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Advancing Artificial Intelligence Framework for Accurate and Early Heart Attack Detection and Evaluation

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Abstract

Cardiovascular diseases (CVDs) represent prevalent chronic conditions that constitute significant threats to global public health. The electrocardiogram (ECG) is a widely utilized noninvasive diagnostic technique that records the dynamic bioelectrical activity of the heart. By employing electrodes affixed to the skin39;s surface, the ECG enables continuous monitoring of the heart's cyclical phases of contraction and relaxation. Atrial fibrillation (AF), characterized by irregular cardiac rhythms and the frequent absence of a discernible P-wave, markedly increases the risk of adverse clinical outcomes if left untreated. These complications include heart failure, ischemic stroke, cardiovascular mortality, thromboembolic events, blood coagulation disorders, and cognitive decline. The asymptomatic and often clinically silent nature of AF presents substantial challenges for early detection, potentially leading to fatal consequences. The manual diagnosis of atrial fibrillation (AF) using electrocardiograms (ECGs) presents notable limitations, as it requires substantial clinical expertise and entails a labor-intensive, time- consuming process. Hence, recent advancements in Artificial Intelligence have had a transformative impact on the domain of cardiovascular diagnostics. This study proposes an automated framework capable of capturing both temporal and frequency features of cardiac signals to facilitate accurate AF classification. The initiative aligns with the broader vision of integrating the Internet of Things (IoT) and AI technologies, thereby establishing a forward-looking model for proactive cardiovascular health monitoring. The classification efficacy of the system was rigorously evaluated using a Support Vector Machine (SVM) algorithm, achieving a classification accuracy of 94% across two categories: Atrial Fibrillation (AF) and Normal Sinus Rhythm (NSR). This novel approach holds substantial promise for deployment in clinical environments, enabling real-time detection of AF during routine ECG assessments, ultimately enhancing patient care while alleviating the diagnostic burden on medical professionals.

Keywords

Machine learning, Deep learning, ECG, Atrial fibrillation, IOT, CNN, LSTM, frequency features, SVM.

Résumé

Les maladies cardiovasculaires (MCV) représentent des affections chroniques répandues constituant des menaces majeures pour la santé publique mondiale. L'électrocardiogramme (ECG) est une technique de diagnostic non invasive largement utilisée qui enregistre l'activité bioélectrique dynamique du cœur. Grâce à des électrodes fixées à la surface de la peau, l'ECG permet une surveillance continue des phases de contraction et de relaxation du cœur. La fibrillation auriculaire (FA), caractérisée par des rythmes cardiaques irréguliers et l'absence fréquente d'une onde P identifiable, augmente considérablement le risque de complications cliniques graves si elle n'est pas traitée. Ces complications incluent l'insuffisance cardiaque, l'accident vasculaire cérébral ischémique, la mortalité cardiovasculaire, les événements thromboemboliques, les troubles de la coagulation sanguine, et le déclin cognitif. Le caractère asymptomatique et souvent silencieux de la FA rend la détection précoce difficile, ce qui peut entraîner des conséquences fatales. Le diagnostic manuel de la fibrillation auriculaire à l'aide de l'ECG présente des limites notables, car il exige une expertise clinique approfondie et constitue un processus long et laborieux. Par conséquent, les récentes avancées en intelligence artificielle ont profondément transformé le domaine du diagnostic cardiovasculaire. Cette étude propose un cadre automatisé capable de capturer les caractéristiques temporelles et fréquentielles des signaux cardiaques afin de permettre une classification précise de la FA. Cette initiative s'inscrit dans la vision globale d'intégration des technologies de l'Internet des objets (IoT) et de l'IA, établissant ainsi un modèle prospectif de surveillance proactive de la santé cardiaque. L'efficacité du système de classification a été rigoureusement évaluée à l'aide de l'algorithme de la machine à vecteurs de support (SVM), atteignant une précision de 94% pour deux catégories : Fibrillation Auriculaire (FA) et Rythme Sinusal Normal (RSN). Cette approche novatrice offre un potentiel considérable pour une application en milieu clinique, permettant la détection en temps réel de la FA lors des examens ECG de routine, tout en améliorant les soins aux patients et en allégeant la charge diagnostique des professionnels de santé.

Mots-clés

Apprentissage automatique, apprentissage profond, ECG, fibrillation auriculaire, IoT, CNN, LSTM, caractéristiques fréquentielles, SVM.

الملخص

تمثل أمراض القلب والأوعية الدموية (CVDs) حالات مزمنة شائعة تشكل تهديدات كبيرة للصحة العامة العالمية. يُعد تخطيط القلب الكهربائي (ECG) تقنية تشخيصية غير جراحية واسعة الاستخدام تسجل النشاط الكهربائي الديناميكي للقلب. من خلال استخدام أقطاب كهربائية تُثبت على سطح الجلد، يتيح تخطيط القلب المتابعة المستمرة لمراحل انقباض القلب وانبساطه. يُعد الرجفان الأذيني (AF)، الذي يتميز بإيقاعات قلبية غير منتظمة وغياب متكرر للموجة P الملحوظة، عاملاً يزيد بشكل كبير من خطر النتائج السريرية السلبية في حال عدم معالجته. تشمل هذه المضاعفات: فشل القلب، السكتة الدماغية الإقفارية، الوفيات القلبية الوعائية، الأحداث التخثرية، اضطرابات تخثر الدم، والتدهور المعرفي. إن الطبيعة اللاعرضية وغالباً الصامتة سريرياً للرجفان الأذيني تطرح تحديات كبيرة للكشف المبكر، مما قد يؤدي إلى عواقب قاتلة.

يشهد التشخيص اليدوي للرجفان الأذيني باستخدام تخطيط القلب الكهربائي محدوديات واضحة، إذ يتطلب خبرة سريرية كبيرة ويعد عملية مجهدة وتستغرق وقتاً طويلاً. ومن هنا، فإن التقدم الحديث في مجال الذكاء الاصطناعي قد أحدث تحولاً كبيراً في مجال تشخيص أمراض القلب. تقترح هذه الدراسة إطاراً آلياً قادراً على التقاط كل من الخصائص الزمنية والترددية للإشارات القلبية لتسهيل تصنيف الرجفان الأذيني بدقة. تتماشى هذه المبادرة مع الرؤية الأشمل لدمج تقنيات إنترنت الأشياء (IoT) والذكاء الاصطناعي، مما يؤسس نموذجاً مستقبلياً للمراقبة الصحية القلبية الاستباقية. تم تقييم فعالية النظام التصنيفي بدقة باستخدام خوارزمية آلة الدعم الناقل (SVM)، حيث حقق النظام دقة تصنيف بلغت 94٪ عبر فئتين: الرجفان الأذيني (AF) والإيقاع الجيبي الطبيعي (NSR). هذا النهج المبتكر يحمل وعوداً كبيرة للتطبيق في البيئات السريرية، مما يتيح اكتشاف الرجفان الأذيني في الوقت الفعلي أثناء الفحوصات الروتينية لتخطيط القلب، ويعزز بذلك جودة الرعاية الصحية ويخفف العبء التشخيصي عن كاهل الأطباء.

الكلمات المفتاحية

تعلم الآلة، التعلم العميق، تخطيط القلب الكهربائي، الرجفان الأذيني، إنترنت الأشياء، الشبكات العصبية الالتفافية (CNN)، الشبكات العصبية المتكررة (LSTM)، الخصائص الترددية، آلة الدعم الناقل (SVM).

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GENERAL INTRODUCTION

Statistics indicate that cardiovascular diseases are responsible for approximately 17.9 million deaths annually[14], highlighting the urgent need for precise and rapid diagnostic systems to facilitate effective medical decision-making. Atrial Fibrillation (AF) is a common form of cardiac arrhythmia that significantly elevates the risk of cerebrovascular events such as stroke, as well as the likelihood of developing heart failure. Traditional heart attack diagnosis relies on the Holter monitor, which records heart activity over an extended period, with data later analyzed by physicians[15]. However, this technique requires significant time, which may delay immediate medical intervention. Therefore, artificial intelligence (AI) has become an effective tool in enhancing the diagnostic process by providing real-time, accurate analysis of cardiac data, reducing human errors, and accelerating medical response. This work focuses on developing an advanced AI framework that utilizes atrial fibrillation (AF) detection as a key indicator for early heart attack diagnosis in real-time[16]where an IoT-enabled ECG monitoring device is used to analyse the ECG signal. The proposed system leverages deep learning and machine learning techniques to analyze electrocardiogram (ECG) signals directly. Once any AF-related abnormalities are detected, physicians are immediately alerted to take necessary actions, enabling urgent medical intervention before a heart attack occurs.

Initial tests of the proposed framework have demonstrated its efficiency, achieving an accuracy rate exceeding 94% in classifying cardiac signals, which confirms its effectiveness in early and real-time atrial fibrillation diagnosis. This study aims to improve medical assessment and enhance timely therapeutic intervention, ultimately reducing mortality rates caused by diagnostic delays. From this standpoint, multiple critical challenges emerge, which the present study seeks to systematically investigate and address:

- The reliance on traditional methods such as the Holter monitor, which requires extended time for analysis and diagnosis.
- The need to develop a highly accurate AI model capable of real-time heart attack detection from ECG signals.
- Comparing the proposed model's performance with conventional methods in terms of accuracy, speed, and diagnostic efficiency.

This thesis is organized into 5 chapters, each addressing a specific aspect of the research problem.

Chapter I : *Initiation to image processing, computer vision and artificial intelligence paradigms*

This chapter introduces fundamental AI concepts, focusing on machine learning and deep learning paradigms.

Chapter II : *Automated detection of Atrial Fibrillation: A focus on the most prevalent cardiac arrhythmia*

This chapter reviews atrial fibrillation as one of the most common cardiac arrhythmia, focusing on automatic detection techniques using artificial intelligence. It also discusses the limitations of traditional methods such as the Holter monitor and emphasizes the need for the development of intelligent models for early and accurate detection. Additionally, it presents previous work in this field and highlights the research problem.

Chapter III : *Iot-based system design for early atrial fibrillation (AF) detection*

This chapter discusses the design of an intelligent system for early detection of atrial fibrillation based on Internet of Things (IoT) technologies. The system relies on an ECG sensor to measure the heart's electrical signals, along with the ESP8266 microcontroller that enables wireless communication. The data is processed and analyzed using artificial intelligence algorithms, allowing users to perform effective real-time health monitoring remotely.

Chapter IV : *Experimental design and model development for atrial fibrillation (AF) detection*

This chapter presents the experimental procedures followed in the development and training of the intelligent model, covering data collection and the selection of algorithms used for model training. The chapter also provides a detailed pipeline of the system's development, highlighting all the steps followed in the project.

Chapter V : *Experimental results and evaluation of the proposed system's performance*

This chapter reviews the integration of the artificial intelligence framework into an Internet of Things-based system, focusing on the tools used in building the project and the communication mechanisms that enable immediate medical intervention. It also presents all the results obtained during the system deployment.

Then, we conclude this work with a general conclusion and future perspectives.

CHAPTER I

INITIATION TO IMAGE PROCESSING, COMPUTER VISION AND ARTIFICIAL INTELLIGENCE PARADIGMS

I.1 Introduction

The advent of deep learning has revolutionized computer vision, with deep neural networks achieving unprecedented performance in fundamental tasks such as image classification, object detection, and segmentation. Over the past decade, the field has witnessed remarkable architectural evolution from convolutional neural networks (CNNs) that dominated early benchmarks, to self-attention mechanisms that captured long-range dependencies, and most recently to vision transformers (ViTs) that have redefined state-of-the-art performance. This chapter systematically examines three pivotal paradigms in modern visual AI: Convolutional Neural Networks: The backbone architecture leveraging spatial hierarchies through inductive biases. Self-Attention Mechanisms: Content-adaptive feature weighting for global context modeling. Vision Transformers: End-to-end sequence modeling that treats images as tokenized patches.

I.2 Backgrounds and Related Work

Artificial Intelligence (AI) and Computer Vision have seen rapid advancements due to the rise of deep learning, particularly Convolutional Neural Networks (CNNs) which revolutionized image classification, detection, and segmentation tasks. Early methods relied heavily on handcrafted features and traditional machine learning, but modern approaches use hierarchical feature learning from large annotated datasets. Architectures such as AlexNet, VGG, ResNet, and DenseNet have progressively improved model depth and representation capacity. Attention mechanisms and transformers have further enhanced vision tasks by modeling long-range dependencies and global context. Vision Transformers (ViTs) and hybrid CNN-attention networks now rival or surpass traditional convolutional architectures in many benchmarks. For segmentation, encoder-decoder frameworks like U-Net and its variants (U-Net++, Attention U- Net) are widely adopted due to their ability to preserve spatial information. Additionally, attention modules like SE-Net and CBAM improve model focus on relevant features. These architectures are foundational in numerous applications such as autonomous driving, medical

imaging, and remote sensing. Current research continues to optimize model efficiency, generalization, and interpretability in vision-based AI systems.

I.2.1 Deep Convolutional Neural Networks

In the rapidly evolving domains of computer vision and image processing, image classification remains a fundamental and persistently challenging task centered on the accurate recognition and categorization of visual content. As digital transformation and automation continue to expand, the demand for intelligent systems capable of interpreting visual data has surged dramatically. The complexity and high dimensionality inherent in image data often limit the effectiveness of traditional machine learning algorithms. In contrast, Convolutional Neural Networks (CNNs) have emerged as a powerful solution, offering superior performance in handling such complexities. Various CNN architectures have been developed, each providing a unique framework for training models tailored to image classification task [17][18]. Deep convolutional neural networks (CNNs) serve as the core framework in numerous computer vision applications, such as object detection [19] [20], image classification [5][21], and image segmentation [22][23][24][25]. A typical CNN architecture, as illustrated in the figure I.1, comprises multiple layers, including convolution, pooling, and batch normalization. Convolution layers are followed by pooling layers to decrease spatial resolution while enhancing the depth through subsequent convolutions. Eventually, fully connected layers are added, along with a SoftMax layer, to generate classification probabilities. The subsequent sections describe each key component of a CNN.

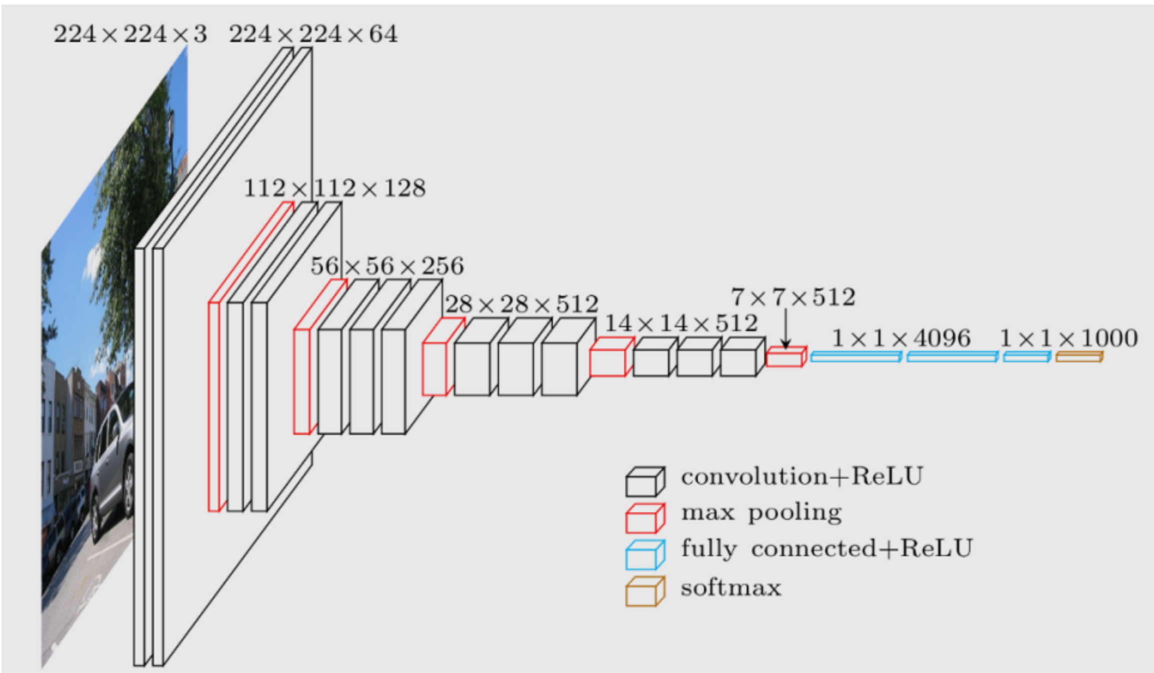


Figure I.1: General Architecture of Convolution Neural Network [1].

- **1. Convolution Layer :** This layer forms the foundational unit of CNNs and contains trainable filters or kernels. Each kernel spans the entire depth of the input and slides over the image, computing a dot product at every spatial location. The resulting values create a two-dimensional activation map that reflects the kernel's response across the input image.

- **2. Pooling Layer :** It is positioned between consecutive convolutional layers, the pooling layer down-scales the spatial dimensions of feature maps. It operates on each channel separately using a defined window size and applies either a max or average function, depending on the pooling method employed.

- **3. Activation Layer :** This layer introduces non-linearity into the CNN: convolutional neural network, which is crucial for identifying intricate features. Below, different of activation functions layer types are outlined.

  - **a. Sigmoid** The sigmoid function produces outputs within the range of 0 to 1. However, a major drawback is its tendency to saturate, which can lead to vanishing gradients. Additionally, its outputs are not centered on zero, which may hinder optimization during training. The sigmoid function is written in the next equation:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{I.1}$$

  - **b. Tanh** The function of hyperbolic tangent (tanh) creates outputs in the range of -1 to 1, producing it zero-centered, which can be valuable for optimization issues. However, like to the function of sigmoid, it is also prone to saturation, a condition in which the activation function yields gradients close to zero for large-magnitude inputs, thereby hindering efficient learning due to vanishing gradients. The mathematical equation of tanh is:

$$\tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{I.2}$$

  - **c. ReLU(Rectified Linear Unit)** The ReLU function outputs zero for any negative input and returns the input itself if it39;s positive. This simplicity makes it computationally efficient and helps mitigate the vanishing gradient issue seen with sigmoid and tanh. However, ReLU is susceptible to the quot;dying ReLUquot; phenomenon, in which certain neurons become inactive by consistently producing zero outputs, thereby ceasing to contribute to the learning process due to negative input values, effectively becoming inactive during training. The mathematical equation of ReLU is:

$$\text{ReLU}(x) = \max(0, x) \tag{I.3}$$

- **d. Leaky ReLU** It addresses the quot;dying ReLUquot; issue by presenting a small, non-zero gradient for negative input values, as illustrated in the corresponding figure. This modification allows the activation function to produce small negative outputs when the input is less than zero, thereby preserving a minimal gradient flow during training. The mathematical equation for Leaky ReLU is given as follows:

$$\text{Leaky ReLU}(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha x & \text{if } x \leq 0 \end{cases} \tag{I.4}$$

- **4. Batch Normalization Layer** The batch normalization layer is typically applied following convolution and activation layers. It standardizes the activations at each layer by normalizing them, thereby improving training stability and convergence. Unlike traditional preprocessing steps, batch normalization is embedded within the network architecture, allowing it to dynamically normalize intermediate outputs during training.

- **5. Fully Connected Layer** In fully connected layers, each neuron establishes a connection with every neuron in the preceding layer. These layers perform a linear transformation on the input vector through matrix multiplication, followed by the addition of a bias term, enabling the network to learn complex feature representations across the entire input space.

I.2.2 Self-Attention Mechanism

Convolutional neural networks are inherently constrained by the limited receptive field determined by the size of the convolutional kernel. To capture long-range dependencies within the network, self-attention mechanisms are commonly integrated following specific convolutional layers [26][27][28].These attention modules enhance feature representation by emphasizing informative regions and suppressing less relevant ones. Based on the dimensionality of their application, attention mechanisms are generally categorized into two

types: (1) Spatial Attention and (2) Channel Attention. The subsequent section presents a unified mathematical formulation of the attention mechanism, independent of the specific dimension on which it operates. Broadly, attention mechanisms can be structured into two main components.

- **Attention Weight Computation** This component involves generating a set of attention weights that quantify the relevance of features either across spatial locations or channels. These weights are calculated using transformations that capture contextual information, such as the relationship between distant spatial elements or inter-channel dependencies.
- **Feature Recalibration** Once the attention weights are computed, they are used to scale the original features accordingly. This selective amplification or suppression of features enhances the model39;s ability to focus on discriminative information while reducing the influence of irrelevant or noisy components.

I.2.3 Vision Transformer

Motivated by the remarkable success of transformer architectures in natural language processing (NLP) and the demonstrated effectiveness of self-attention mechanisms within convolutional neural networks (CNNs), vision transformers have gained significant traction in the field of computer vision[29][30][31]. These models have achieved performance comparable to, and in some cases surpassing, that of traditional CNN-based approaches. At the core of the transformer architecture based on the multi-head self-attention [28]. The following Figure I.2 illustrates the Attention Blocks Architecture: a- Scaled Dot-Product Attention b- Multi-Head Attention

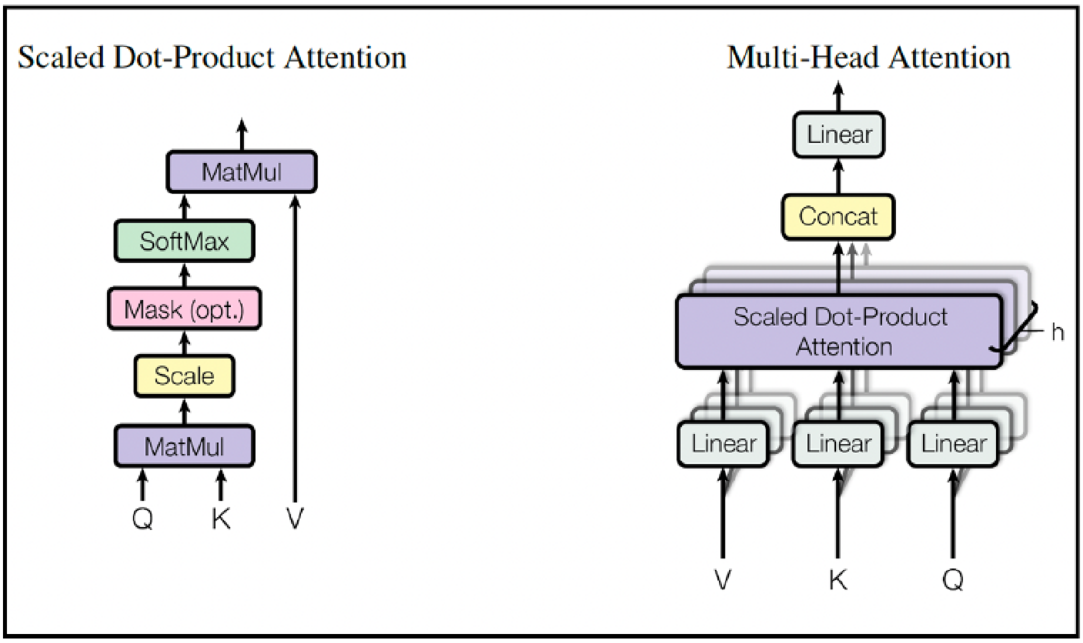


Figure I.2: Attention Blocks Architecture: a-Scaled Dot Product Attention b-Multi Head attention[2]

1. Multi-Head Attention

To overcome the representational limitations of single-head attention, the multi-head self-attention mechanism enhances model capacity by projecting the input into multiple lower-dimensional subspaces. Each of these subspaces is processed by an independent attention head in parallel, enabling the model to capture diverse contextual relationships across different representation subspaces. The outputs from all attention heads are then concatenated and linearly transformed to produce the final output representation. This design improves the network's ability to model complex dependencies and enhances its expressive power.

Let $\mathbf{X} \in \mathbb{R}^{n \times d_{\text{model}}}$ be the input sequence, where n is the sequence length and d_{model} is the feature dimension. For each of the h attention heads, the input is projected into query $\mathbf{Q}$, key $\mathbf{K}$, and value $\mathbf{V}$ matrices:

$$\text{head}_i = \text{Attention}_i(\mathbf{Q}_i, \mathbf{K}_i, \mathbf{V}_i) = \text{Softmax}\left(\frac{\mathbf{Q}_i \mathbf{K}_i^T}{\sqrt{d_k}}\right) \mathbf{V}_i \tag{I.5}$$

Where:

$$\mathbf{Q}_i = \mathbf{X}\mathbf{W}_i^Q, \quad \mathbf{K}_i = \mathbf{X}\mathbf{W}_i^K, \quad \mathbf{V}_i = \mathbf{X}\mathbf{W}_i^V \tag{I.6}$$

$$\mathbf{W}_i^Q, \mathbf{W}_i^K, \mathbf{W}_i^V \in \mathbb{R}^{d_{\text{model}} \times d_k}, \quad d_k = \frac{d_{\text{model}}}{h} \tag{I.7}$$

The outputs from all heads are concatenated and passed through a final linear projection:

$$\text{MultiHead}(\mathbf{X}) = \text{Concat}(\text{head}_1, \text{head}_2, \ldots, \text{head}_h)\mathbf{W}^O \tag{I.8}$$

Where $\mathbf{W}^O \in \mathbb{R}^{d_{\text{model}} \times d_{\text{model}}}$ is a learnable output projection matrix.

As the transformer architecture is inherently designed to process sequential data, input images are initially partitioned into a series of fixed-size patches, which are then treated as tokens and fed into a stack of transformer layers. Specifically, an image is divided into a grid of non-overlapping two-dimensional patches, each of which is flattened into a vector and linearly embedded. These patch embeddings form the input sequence for the transformer, where the total number of patches corresponds to the effective sequence length.

The Vision Transformer (ViT) architecture is composed of a series of transformer blocks, each consisting of a multi-head self-attention mechanism followed by a multilayer perceptron (MLP). The MLP module typically includes two fully connected layers separated by a non-linear activation function, such as the Gaussian Error Linear Unit (GELU). To stabilize training and improve performance, Layer Normalization is applied prior to each block, and residual connections are incorporated around both the attention and MLP components. This hierarchical structure enables the model to capture both local and global contextual relationships across the input image patches.

I.3 Computer Vision Processing

I.3.1 Image Classification

Image classification involves assigning a predefined category label to a given image and represents a foundational task in the field of computer vision. It serves as a fundamental component in numerous advanced applications, often functioning as the backbone of more complex systems. Over time, a variety of deep learning-based models have been developed for this purpose[21][25]. Based on the principal architectural elements, these classification models can be broadly categorized into three groups: convolutional neural networks (CNNs), self- attention-enhanced convolutional networks, and transformer-based architectures. In the following sections, we provide a brief overview of representative models from each of these categories[32][33].

- **1. Convolutional Networks**

Numerous studies have focused on enhancing the performance of convolutional networks by modifying architectural components such as increasing network depth or width, incorporating skip connections, and experimenting with alternative convolutional operations. Below, we provide a concise overview of several key classification models developed within this framework.

– **a. ResNet**

ResNet, introduced by [32], was the first deep neural network architecture to successfully scale beyond 100 layers. To mitigate the vanishing gradient problem commonly encountered in very deep networks, ResNet incorporates residual learning through the use of identity-based skip connections. These residual connections allow the network to propagate information directly from one layer to the next without modification, thereby facilitating the training of deeper models. Each residual block in ResNet consists of a sequence of three convolutional layers, where a 3×3 convolution is stacked by two 1×1 convolutions. The 1×1 convolutions serve to adjust the dimensionality of the feature maps, particularly the number of channels. A variant of ResNet with 152 layers demonstrated state-of-the-art performance on the ImageNet benchmark, achieving a top-5 error rate of just 4.49% and a top-1 error rate of 19.38%. The following FigureI.3 illustrates ResNet based Residual block Architecture

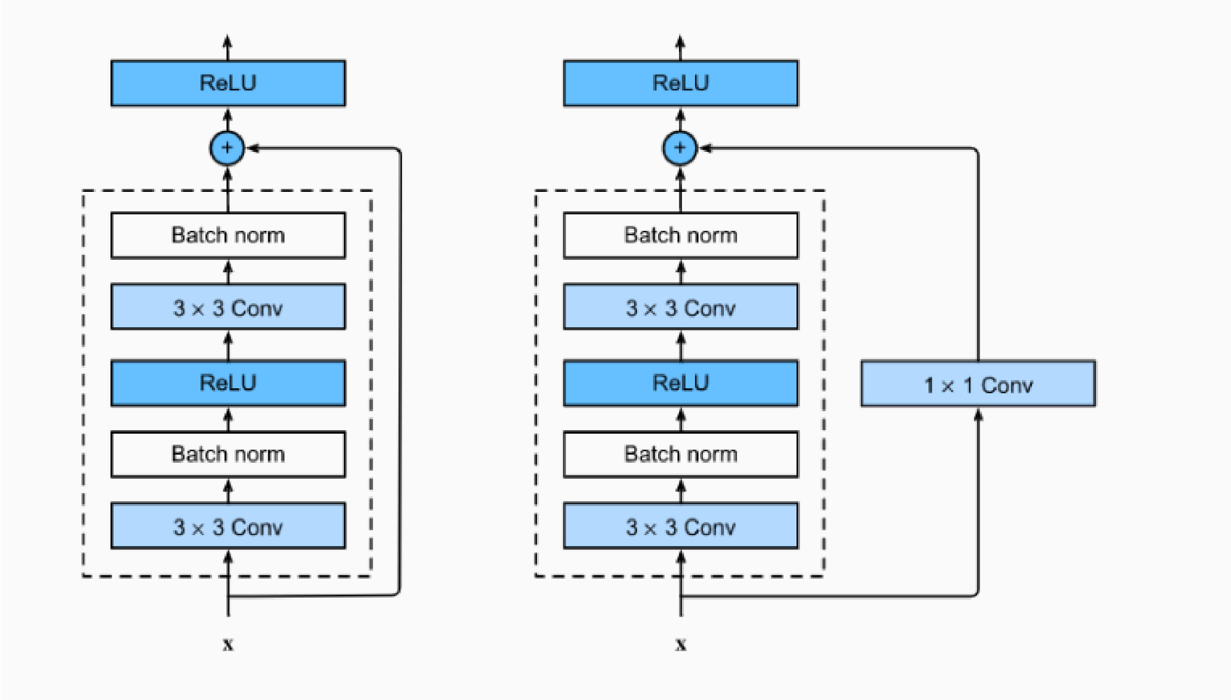


Figure I.3: ResNet based Residual block Architecture [3].

– **b. Wide-ResNet**

Wide-ResNet, proposed by [25], retains the residual block structure introduced in the original ResNet architecture. However, instead of increasing network depth, Wide-ResNet demonstrates that performance can be significantly improved by expanding the width of the network (i.e., increasing the number of channels in each layer) while simultaneously reducing the overall number of layers. This modification not only maintains competitive accuracy with deeper ResNet models but also simplifies the training process.The following FigureI.4 illustrates ide-ResNet based ResNet: Residual block Architecture

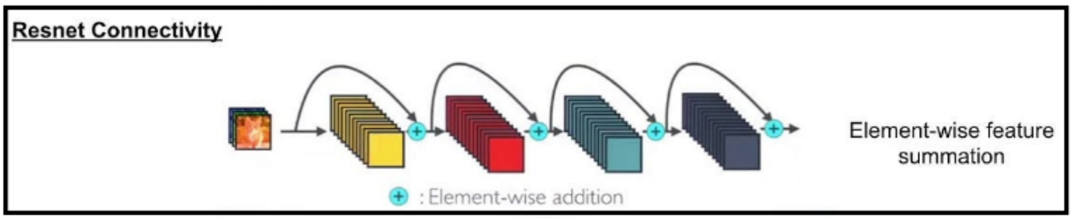


Figure I.4: Wide-ResNet based ResNet: Residual block Architecture[4].

– **c. DenseNet**

DenseNet, introduced by [34], is based on the observation that convolutional networks are more efficient and easier to optimize when there are shorter and more direct connections between early and later layers in the network. To exploit this, DenseNet employs a novel connectivity pattern in which each layer receives, as input, the concatenated feature maps of all preceding layers within the same dense block. Conversely, the output of each layer is propagated forward to all subsequent layers. This dense connectivity scheme differs from traditional architectures such as ResNet, which rely on element-wise addition for feature aggregation. Instead, DenseNet utilizes feature concatenation, promoting feature reuse and encouraging more efficient information and gradient flow throughout the network. Moreover, DenseNet requires fewer filters per layer, resulting in a more compact and parameter-efficient architecture. As a result, it achieves superior performance on various image classification benchmarks when compared to both ResNet and Wide-ResNet, while also offering improved training efficiency.The following FigureI.5 illustrates DenseNet Residual block Architecture

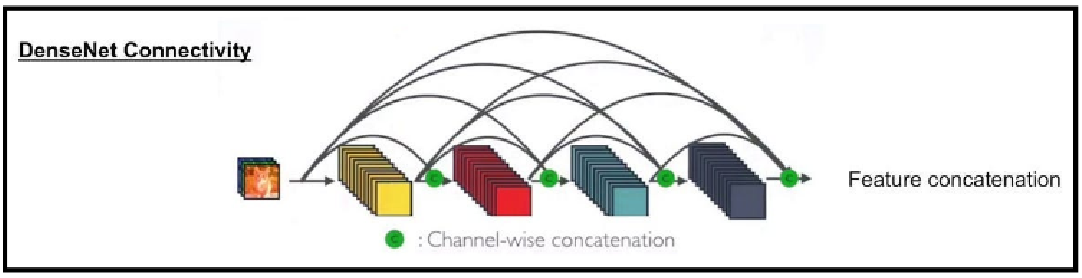


Figure I.5: DenseNet Residual block Architecture[4].

- **d. Inception** The Inception architecture, introduced by [33] was designed to address two critical challenges in deep neural networks: overfitting and excessive model complexity due to a

  large number of parameters. The overall architecture is organized into three principal components:

  - **Stem:** Serving as the initial stage following the input layer, the stem comprises standard convolutional layers combined with ReLU activation functions, as well as max pooling operations to progressively reduce spatial dimensions.
  - **Output Classifier:** Positioned at the end of the network, this component

processes the flattened feature maps through one or more fully connected layers, concluding with a softmax activation function to generate class probabilities.

* **Inception Module:** Occupying the central portion of the architecture, the inception module represents the core innovation of the network. It introduces a parallel processing structure that distinguishes it from conventional architectures by enabling multi-scale feature extraction.As illustrated in the figure I.6

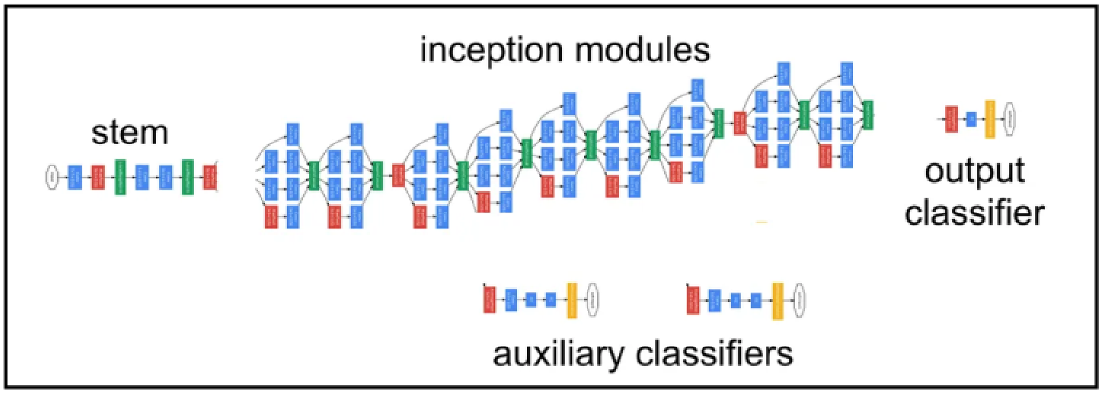


Figure I.6: Inception Network General Architecture[5].

– **e. MobileNet**

MobileNet, proposed by Howard et al. (2017), is a highly efficient and lightweight neural network architecture specifically designed to operate under constrained computational environments by significantly reducing the number of parameters and operations. Its core innovation lies in the use of depthwise separable convolutions, which decompose the standard convolution operation into two distinct stages: depthwise convolution and pointwise convolution. In the depthwise convolution phase, a single convolutional filter is applied independently to each input channel, performing spatial filtering without inter-channel mixing. This is followed by the pointwise convolution, which uses 1×1 convolutions to linearly combine the output of the depthwise stage across channels, effectively projecting the spatially filtered outputs into a new feature space. This decomposition drastically reduces computational complexity and parameter count compared to conventional convolution, making MobileNet particularly well-suited for mobile and embedded vision applications.As illustrated in the figure I.8

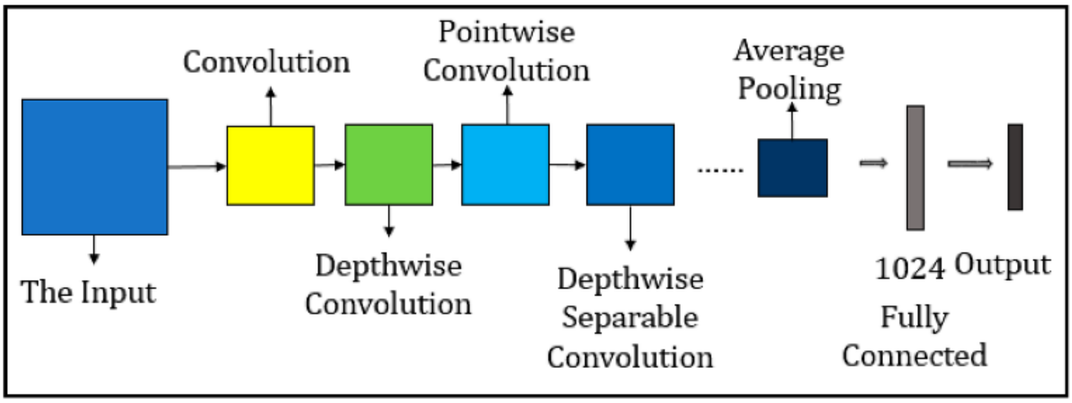


Figure I.7: MobileNet Network General Architecture [5].

- **2. Augmented Self-Attention Convolution Network**

  A range of spatial and channel-wise self-attention mechanisms has been proposed in the literature [27][28][35][36]to enhance feature representation by emphasizing informative regions of the input while attenuating less relevant ones. In the following sections, we provide a brief overview of several prominent attention mechanisms within this context.

  - **a. Squeeze-and-Excitation Network (SE-Net):** [26] introduced the Squeeze-and-Excitation (SE) block, a channel-wise attention mechanism designed to be integrated into convolutional neural networks following each stage. The SE block enhances representational capacity by adaptively recalibrating channel-wise feature responses, emphasizing the most informative features while diminishing less relevant ones. It operates through two sequential processes: squeeze and excitation. The squeeze phase performs global average pooling across spatial dimensions to capture channel-wise global statistics, effectively summarizing the feature map into an n-dimensional descriptor. This descriptor is then passed through a lightweight bottleneck structure composed of two fully connected layers during the excitation phase, producing a set of modulation weights. These weights are subsequently used to re-scale the original feature maps, thereby enabling dynamic channel-wise feature recalibration.As illustrated in the figure I.8

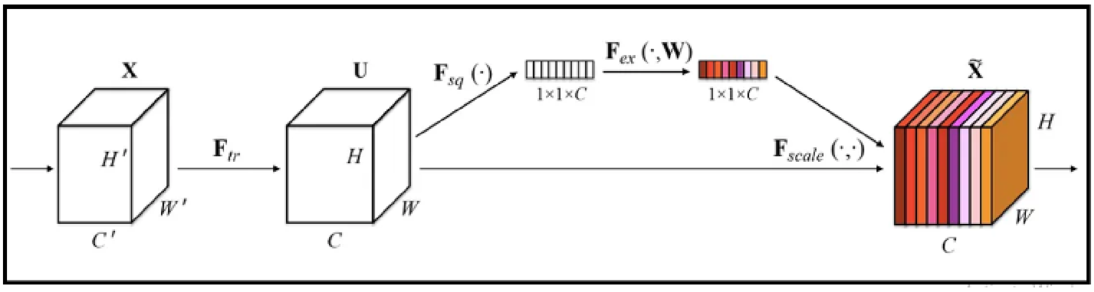


Figure I.8: Squeeze-and-Excitation Network (SE-Net) General Architecture [6].

- **b. Convolutional Block Attention Module (CBAM):**

  this is proposed by [37], is a lightweight and modular attention mechanism that sequentially applies channel and spatial attention to refine intermediate feature representations in convolutional neural networks. The channel attention module exploits both global max pooling and global average pooling to capture diverse contextual information across channels. These pooled descriptors are processed through a shared multi-layer perceptron (consisting of two fully connected layers) to generate adaptive weights that modulate each channel accordingly. Subsequently, the spatial attention module enhances salient regions in the spatial domain by first concatenating the channel-refined feature maps obtained from max and average pooling operations along the channel axis. This concatenated representation is then passed through a convolutional layer with a 7×7 kernel, followed by a sigmoid activation function to generate a spatial attention map that emphasizes important spatial locations.The following Figure I.9 illustrates CBAM General Architecture

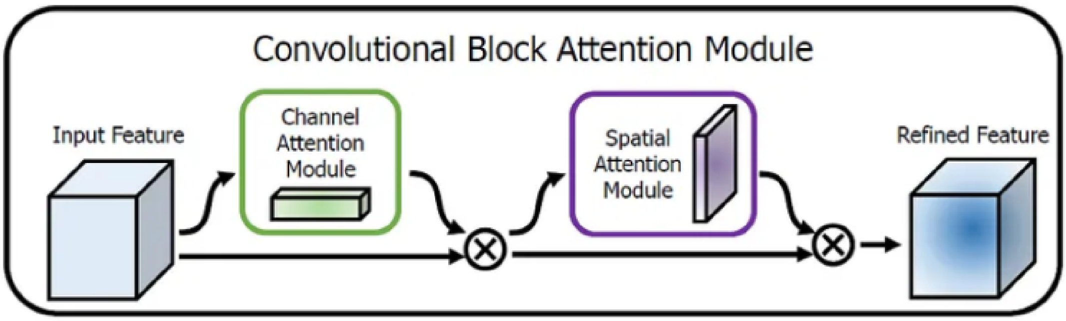


Figure I.9: CBAM General Architecture [7].

I.3.2 Image segmentation

Image segmentation is a fundamental task in computer vision that involves assigning a categorical label to each pixel in an image. The goal is to partition an image into semantically meaningful regions, such as separating objects from the background or distinguishing between different object classes. Deep learning has significantly advanced the performance of image segmentation models, especially in handling complex scenes and high-dimensional data.

One of the most widely used approaches for segmentation is the encoder-decoder architecture, which has proven effective across a broad range of domains, from medical imaging to autonomous driving and scene understanding. In this architecture, the encoder is responsible for capturing high-level semantic features by progressively reducing the spatial dimensions through layers of convolution, activation, and pooling operations. Conversely, the decoder restores the resolution of the feature maps to the original input size using upsampling techniques, such as transposed convolutions or interpolation, followed by additional convolutions. To enhance feature preservation, skip connections are often employed between corresponding encoder and decoder layers, allowing the model to retain fine-grained spatial details critical for accurate segmentation.

Despite the effectiveness of standard architectures such as U-Net [23], various challenges persist in general image segmentation tasks, including variations in object scale, occlusion, lighting conditions, and background clutter. Consequently, numerous enhancements and architectural variants have been proposed (e.g., UNet++, DeepLab, SegNet), each aiming to improve segmentation accuracy and generalizability by integrating mechanisms such as atrous convolutions, attention modules, or multi-scale feature fusion.

- **1. U-Net Architecture**

  U-Net, introduced by [23] is a U-shaped deep neural network architecture specifically designed for image segmentation tasks. It is composed of two main components: an encoder (contracting

  path) and a decoder (expanding path). The network receives an image as input and outputs a corresponding segmentation mask. The encoder is structured as a sequence of encoding blocks, where each block comprises a 3×3 convolutional layer, followed by a ReLU activation and batch normalization. These operations are succeeded by a 2×2 max pooling layer, which progressively reduces the spatial resolution of the feature maps while simultaneously doubling the number of channels at each stage, thereby capturing increasingly abstract representations. The decoder mirrors the encoder39;s structure in reverse. Each decoding block includes an upsampling operation (typically via transposed convolution or interpolation), followed by a convolutional layer. To preserve spatial information lost during downsampling, feature maps from the corresponding encoder layers are concatenated with those in the decoder through skip connections. This is followed by a stack of 3×3 convolution and ReLU activation layers. Finally, a 1×1 convolution layer is employed at the output to map the feature maps to the desired number of segmentation classes.As illustrated in the figure I.10.

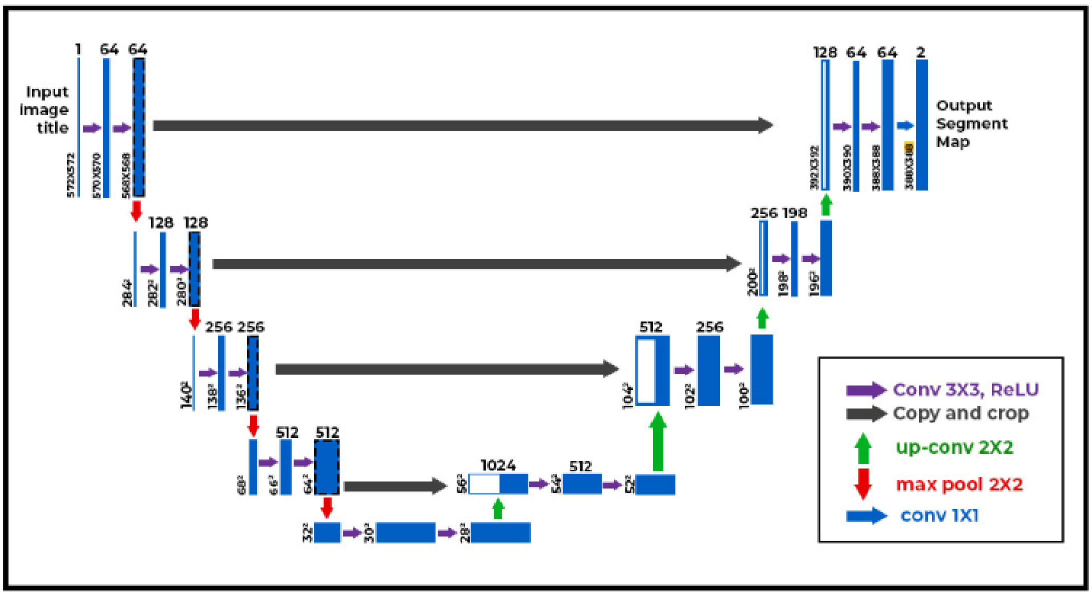


Figure I.10: UNet General Architecture [8].

- **2. U-Net++ Architecture**

U-Net++ addresses the limitations of the original U-Net architecture, particularly the significant semantic disparity between encoder and decoder feature maps, which are directly concatenated in U-Net. To mitigate this issue, U-Net++ introduces nested and densely connected skip pathways, which progressively bridge the semantic gap by enabling feature refinement through intermediate convolutional layers prior to fusion with decoder features. Moreover, U-Net++ incorporates deep supervision, applying auxiliary loss functions at multiple levels within the network. This strategy enhances gradient flow and encourages the model to learn more discriminative representations at various depths, as opposed to relying solely on a final loss computed at the network's output [38].As illustrated in the figure I.11

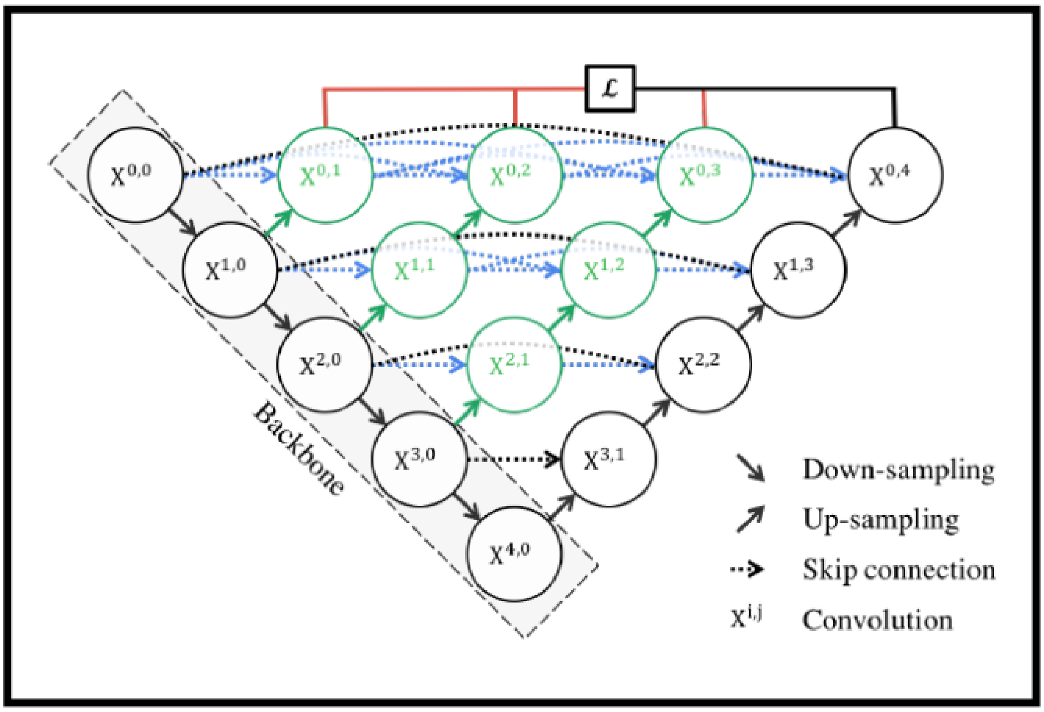


Figure I.11: UNet++ General Architecture [8].

I.4 Applications of artificial intelligence (AI)

- **1. Healthcare :** AI is used in healthcare to improve disease diagnosis, prediction, and personalized treatment by analyzing medical data through machine learning techniques. Example: CNNs are used to analyze X-ray images for accurate heart disease diagnosis [39].

- **2.Natural Language Processing (NLP) :** AI powers applications such as machine translation, sentiment analysis, summarization, and conversational agents Example: BERT is used in sentiment analysis on social media to help businesses understand customer opinions [40].

- **3. Computer Vision :** Computer vision is a branch of AI that enables computers to "see" and understand images and videos, using models like Convolutional Neural Networks (CNNs) and Transformers to analyze visual data. Example: Autonomous vehicles use computer vision to recognize traffic signs and obstacles in real time [41].

- **4. Autonomous Systems :** AI controls drones, self-driving cars, and robotics by integrating computer vision, sensor fusion, and reinforcement learning. Example:Drones use AI technologies to navigate and avoid obstacles without human control [42].

- **5. Cybersecurity :** AI is applied in cybersecurity for threat detection, malware analysis, and identifying anomalies in network traffic, enhancing systems' ability to counter cyberattacks. Example: Deep learning models are used in Intrusion Detection Systems (IDS) to detect cyber threats in real time [43].

I.5 Conclusion

Artificial Intelligence (AI) has emerged as an indispensable tool across virtually every research discipline. From biology and healthcare to engineering, finance, and the humanities, AI-driven methodologies are transforming how knowledge is discovered, data is interpreted, and solutions are implemented. Its ability to automate complex tasks, uncover hidden patterns, and support intelligent decision-making has made it a fundamental asset in modern scientific inquiry. Furthermore, AI39;s integration into core processes from diagnostics in medicine to autonomous systems in robotics demonstrates its adaptability and broad applicability. As data volumes and computational resources continue to grow, the reliance on AI for innovation, optimization, and prediction becomes not just beneficial, but essential. In this context, AI is no longer a niche domain; it is a cornerstone technology shaping the future of research and application.

CHAPTER II

AUTOMATED DETECTION OF ATRIAL FIBRILLATION: A FOCUS ON THE MOST PREVALENT CARDIAC ARRHYTHMIA

II.1 Introduction

Atrial Fibrillation (AF) is a common cardiac arrhythmia that significantly elevates the likelihood of stroke and heart failure, increasing their incidence by approximately fivefold and threefold, respectively. Early and accurate diagnosis, comprehensive risk stratification, and well-informed therapeutic strategies are essential for mitigating its burden and improving patient prognoses. Pharmacological interventions play a crucial role in symptom management and in reducing the risk of serious complications. Although standard electrocardiography has long been the primary diagnostic tool for AF, recent progress in Deep Learning (DL) methodologies has markedly transformed detection capabilities. These advancements facilitate more precise and efficient identification of AF across a range of physiological signals, such as photoplethysmographic data and echocardiographic imaging.

II.2 Cardiovascular diseases (CVDs)

The human heart plays a fundamental role in sustaining life by continuously circulating blood throughout the body, functioning in a manner comparable to a mechanical pump with an average frequency of approximately 72 beats per minute. According to the World Health Organization (WHO), cardiovascular diseases (CVDs), encompassing both vascular and non-vascular conditions, continue to represent a leading global cause of mortality, accounting for an estimated 17.9 million deaths annually [44] [45]. Insights from the Framingham Heart Study over the past five decades have documented a threefold rise in the prevalence of Atrial Fibrillation (AF), positioning it as an emerging cardiovascular epidemic of the 21st century. This trend parallels increasing global life expectancy and extended survival in individuals living with chronic illnesses [46].

II.2.1 Cardiac imaging for cardiovascular diseases (CVDs) detection

As illustrated in Figure II.2.1 cardiovascular diseases (CVDs) are divided into two principal groups: non-vessel structures and vessel structures [45].

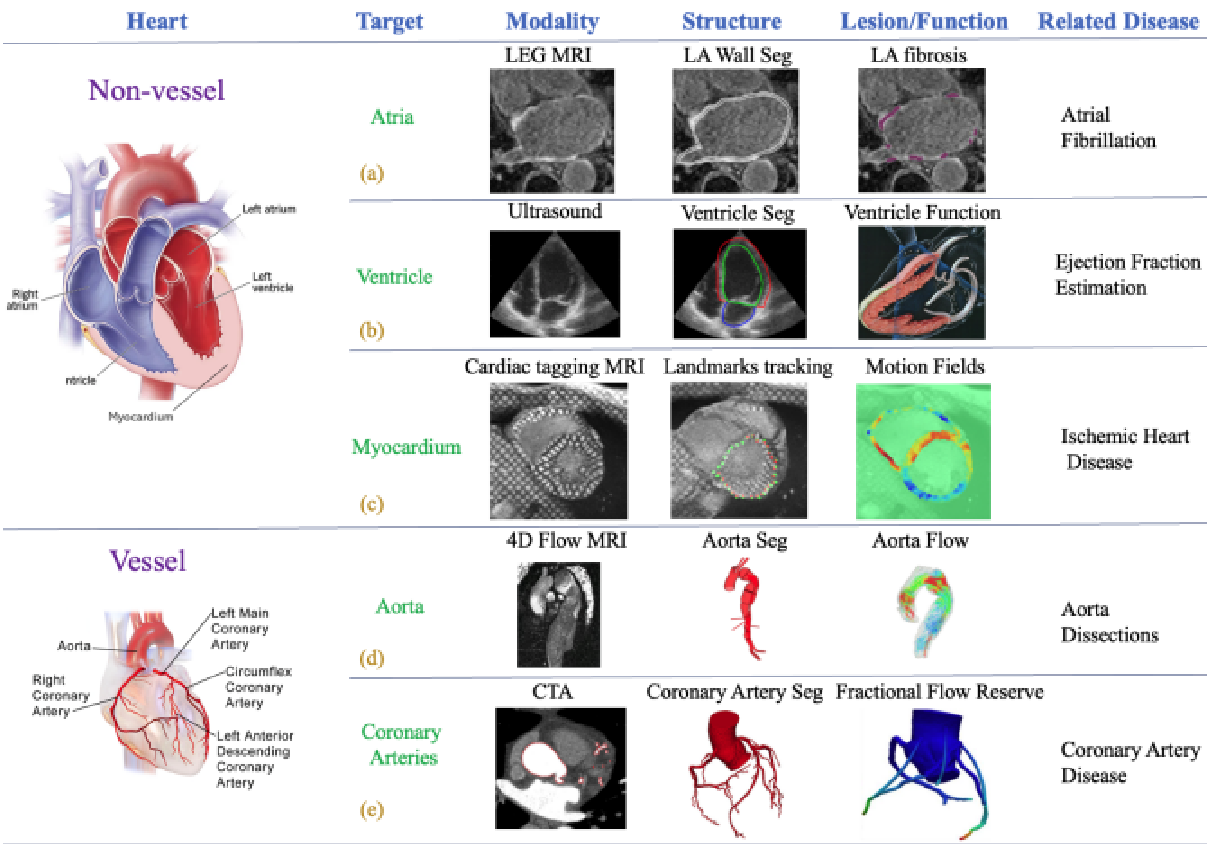


Figure II.1: Cardiovascular diseases (CVDs) categorization. Top: examples of non-vessel anatomical structures, such as (a) atria, (b) ventricles and (c) Myocardium. Bottom: examples of vessel structures, including the (d) aorta and (e) coronary arteries. Source [45]

II.2.1.1 Electrocardiogram (ECG)

An electrocardiogram (ECG) constitutes a vital diagnostic procedure in clinical cardiology, designed to record the heart's electrical activity over time. Represented graphically, the ECG depicts temporal progression on the x-axis and the amplitude of electrical signals on the y-axis, effectively serving as a form of physiological imaging that visualizes cardiac electrical dynamics through characteristic waveform patterns. To acquire this data, electrodes are meticulously affixed to the patient's skin, enabling the detection of bioelectric impulses generated during the cyclical contraction and relaxation of myocardial tissue. The initiation of each cardiac cycle begins with an electrical stimulus from the sinoatrial (SA) node, the heart's natural pacemaker. This impulse propagates through the myocardium, inducing coordinated contractions that facilitate blood circulation. The ECG apparatus captures and amplifies these electrical signals, rendering them as waveforms that offer a comprehensive depiction of cardiac electrical function. As a cornerstone of cardiovascular diagnostics, the ECG provides clinicians with real-time insights into electrophysiological activity, proving indispensable in the detection and evaluation of various cardiac pathologies, including :

- **Cardiac Arrhythmias :** The ECG is a primary tool for identifying irregular heart rhythms, such as atrial fibrillation and ventricular tachycardia.
- **Myocardial Infarction and Ischemia :** It plays a crucial role in detecting ischemic changes and infarction-related anomalies, which are hallmarks of acute coronary syndromes.
- **Structural Cardiac Disorders :** . ECG waveforms may also reflect morphological abnormalities of the heart, including cardiomyopathies and hypertrophic alterations, through distinctive electrical signatures.

II.2.1.2 Cardiac X-ray Imaging

Cardiac X-ray imaging, most notably utilized in coronary angiography, is a diagnostic modality that leverages X-ray technology to generate two-dimensional visualizations of the heart and its vascular structures. Owing to its rapid acquisition time and relatively low radiation dose, it is particularly advantageous in acute clinical scenarios for preliminary evaluation, offering a favorable safety profile for a broad patient population. This imaging technique is especially effective in the detection of coronary artery disease (CAD), as it enables direct visualization of the coronary vasculature. The detailed anatomical information it provides is instrumental in guiding interventional strategies such as percutaneous coronary angioplasty or stent placement to re-establish adequate myocardial perfusion.

II.2.1.3 Cardiac Computed tomography (CT)

Cardiac Computed Tomography (CT) employs advanced X-ray technology to generate high-resolution, cross-sectional, three-dimensional reconstructions of the heart and adjacent vascular structures. While it entails a higher radiation dose compared to conventional cardiac X-ray imaging, Cardiac CT provides superior anatomical detail and spatial resolution. This modality is especially beneficial for comprehensive evaluation of cardiac morphology, with particular emphasis on the coronary arteries. It serves a pivotal role in the non-invasive detection of arterial stenosis or occlusion, critical markers in the diagnosis and risk stratification of coronary artery disease (CAD).

II.2.1.4 Cardiac Ultrasound (Echocardiography))

Cardiac ultrasound imaging, commonly referred to as echocardiography, is a cornerstone in cardiovascular diagnostics, utilizing high-frequency sound waves to generate dynamic, real-time visualizations of the heart. This modality enables detailed assessment of cardiac morphology, chamber dimensions, functional performance, and hemodynamic parameters. Its non-invasive nature, absence of ionizing radiation, and capacity for immediate bedside application make echocardiography the diagnostic modality of choice for initial evaluation across a broad spectrum of cardiac pathologies. It is particularly indispensable in the diagnosis and management of conditions such as valvular heart disease, cardiomyopathies, and congenital cardiac anomalies. In the context of vascular imaging, Intravascular Ultrasound (IVUS) represents a specialized technique in interventional cardiology that provides high-resolution cross-sectional images of the coronary arteries from within the vessel lumen. This intraluminal perspective is critical for assessing plaque burden, vessel wall morphology, and guiding percutaneous coronary interventions with enhanced precision.

II.2.1.5 Nuclear Cardiology

Nuclear imaging in cardiology involves the administration of minute quantities of radiotracers into the bloodstream, which emit gamma radiation detectable by specialized gamma cameras to construct detailed images of cardiac structure and function. As key non-invasive modalities, nuclear cardiology techniques, notably Single-Photon Emission Computed Tomography (SPECT) and Positron Emission Tomography (PET), have played a pivotal role in the diagnosis and management of individuals with confirmed or suspected cardiovascular disease. Cardiac SPECT is a critical imaging technique employed to evaluate myocardial perfusion and ventricular function. Through the acquisition of tomographic images, it provides valuable insights into cardiac anatomy, blood flow distribution, and functional integrity. Its non-invasive nature,combined with its diagnostic utility, renders SPECT indispensable for the detection, monitoring, and therapeutic planning of various cardiovascular disorders. Cardiac PET, on the other hand, represents a highly sophisticated nuclear imaging approach that assesses myocardial metabolism and perfusion with exceptional sensitivity and specificity. By utilizing positron-emitting radiotracers and advanced imaging algorithms, PET facilitates the precise detection of coronary artery disease, delineation of myocardial viability, and evaluation of overall cardiac function. Its superior spatial and temporal resolution enables clinicians to differentiate between ischemic and infarcted tissue, thereby informing critical decisions in the management of complex cardiac conditions.

II.2.1.6 Cardiac Magnetic Resonance Imaging (MRI)

Cardiac Magnetic Resonance Imaging (MRI) is a non-invasive, high-resolution imaging modality that utilizes strong magnetic fields and radiofrequency waves to generate comprehensive visualizations of the heart's anatomy, function, and perfusion. It serves as an essential tool in the assessment of a broad spectrum of cardiovascular pathologies by providing detailed morphological and functional information without the use of ionizing radiation. Cine MRI enables dynamic visualization of the heart throughout the cardiac cycle by acquiring sequential images, effectively capturing the motion of the beating heart in real time. This technique facilitates precise evaluation of cardiac chamber size, ventricular wall motion, and ejection fraction, and is particularly useful in identifying pathological conditions such as ventricular hypertrophy, myocardial infarction, and valvular disorders. Cardiac Tagging MRI (t-MRI), also referred to as myocardial tagging, introduces a grid or tagging pattern onto myocardial tissue during image acquisition, enabling the assessment of myocardial motion and deformation over time. These tags deform with the contraction and relaxation of the myocardium, allowing for quantification of both global and regional myocardial function. Recognized as the gold standard for evaluating myocardial strain and regional deformation, t-MRI plays a critical role in the diagnosis and management of conditions such as ischemic heart disease and dilated cardiomyopathy, as well as in advanced cardiovascular research. T2-weighted MRI, characterized by its sensitivity to variations in tissue water content, offers superior contrast resolution that is instrumental in detecting pathological changes such as inflammation, edema, and ischemia. This imaging sequence is particularly effective for identifying myocardial edema, a hallmark of acute inflammatory or ischemic injury, and provides essential diagnostic information that informs timely clinical intervention.

II.3 Non-vessels cardiovascular diseases

II.3.1 Atria

The atria, comprising the left and right chambers, are situated at the upper portion of the heart and are primarily responsible for receiving blood, as illustrated in Figure II.2.1(a) . The right atrium receives deoxygenated blood from the systemic circulation, while the left atrium accepts oxygenated blood from the pulmonary circulation. Both chambers play an essential role in directing blood into the ventricles. Common pathologies affecting the atria include [45]:

- Atrial Fibrillation (AF), a widespread cardiac arrhythmia, is characterized by disorganized and rapid electrical activity in the atria. Rather than contracting in a coordinated manner, the atria fibrillate, resulting in an irregular heartbeat that can manifest as palpitations, dyspnea, fatigue, and dizziness. Importantly, AF increases the risk of stroke, primarily due to the potential for thrombus formation within the atria. To diagnose AF-related abnormalities, common imaging techniques include ECG and cardiac MRI. While ECG is the preferred method due to its ability to provide real-time monitoring, cardiac MRI, particularly Late Gadolinium Enhancement (LGE) MRI, offers high-resolution imaging critical for evaluating structural alterations and myocardial fibrosis.
- Atrial Enlargement (AE) is another prevalent condition characterized by the enlargement of one or both atria, typically resulting from chronic conditions such as hypertension and heart valve diseases. AE is associated with an elevated risk of arrhythmias and heart failure. A range of imaging techniques, including ECG, echocardiography, cardiac MRI, and CT scans, are utilized to detect and assess AE. ECG is commonly employed for its real-time capability and broad accessibility, effectively identifying atrial size and function. Doppler echocardiography complements ECG by providing detailed hemodynamic information. Cardiac MRI and CT scans, owing to their high spatial resolution, enable precise quantification of atrial volume, offering enhanced sensitivity and specificity in detecting AE.

II.3.2 Ventricle

The heart's ventricles, consisting of the left and right chambers, are fundamental components of its structure, as depicted in Figure II.2.1(b). The left ventricle, the largest and most powerful chamber, plays a pivotal role in receiving oxygenated blood from the left atrium and pumping it into the systemic circulation, thereby ensuring the delivery of oxygen and nutrients to the body's tissues and organs. In contrast, the right ventricle receives deoxygenated blood from the right atrium and pumps it into the pulmonary circulation for oxygenation in the lungs.

Ventricular Diseases encompass a variety of structural and functional anomalies, each carrying distinct clinical consequences. For instance, arrhythmias originating in the ventricles can range from benign conditions, such as premature ventricular contractions (PVCs), to more severe disorders like ventricular tachycardia or ventricular fibrillation. These arrhythmias disrupt the heart's normal pumping function and, in severe cases, may result in life-threatening complications. Conversely, a Ventricular Septal Defect (VSD) is a congenital anomaly marked by an abnormal opening in the septum separating the ventricles, leading to the mixing of oxygenated and deoxygenated blood, which compromises the heart's efficiency. The size and severity of a VSD can vary significantly. As depicted in Figure II.2.1 (b), the Ejection Fraction (EF) serves as a crucial metric for assessing the heart's pumping ability, particularly that of the left ventricle. EF is integral to identifying individuals at risk of heart failure, as it quantifies the percentage of blood ejected from the left ventricle with each contraction. Under normal conditions, the left ventricle pumps out more than 50¨% of its blood volume with each beat. A reduced EF indicates diminished cardiac output and impaired ventricular function.

II.3.3 Myocardium

The myocardium, the muscular middle layer of the heart wall as illustrated in Figure II.2.1(c), is integral to cardiac function. Composed of specialized cardiac muscle cells known as cardiomyocytes, the myocardium is directly responsible for the heart's rhythmic contractions and relaxations, which are essential for effective blood circulation. This muscular layer ensures the propulsion of blood from the heart chambers into the systemic and pulmonary circuits with each heartbeat. The myocardium receives oxygen and vital nutrients via the coronary arteries, which are indispensable for sustaining its metabolic demands.

Given its pivotal role, the myocardium is susceptible to a range of pathological conditions that can compromise cardiac performance and overall cardiovascular health.

a) Myocardial Diseases: One of the most critical disorders is Myocardial Infarction (MI), commonly known as a heart attack. MI occurs when a blockage, typically due to a thrombus in a coronary artery, disrupts blood flow to a segment of the myocardium. This ischemia can lead to cellular damage or necrosis, presenting clinically as chest pain, dyspnea, and in severe cases, life-threatening complications.

b) Cardiomyopathies: Cardiomyopathies represent another major category of myocardial pathology, encompassing a spectrum of structural and functional myocardial abnormalities. A prominent example is Hypertrophic Cardiomyopathy (HCM), a genetic condition characterized by abnormal thickening of the myocardial wall, particularly within the left ventricle. This hypertrophy may impair ventricular filling and outflow, leading to clinical manifestations such as angina, exertional dyspnea, syncope, and arrhythmias. Importantly, HCM is recognized as a leading cause of sudden cardiac death, particularly among young and otherwise healthy individuals.

II.4 Vessel cardiovascular Diseases

II.4.1 Aorta

The aorta, the largest artery in the human body, plays an essential role in the circulatory system, as illustrated in Figure II.2.1(d). Emerging from the left ventricle, it is responsible for distributing oxygenated blood to all bodily tissues, thereby ensuring the delivery of vital nutrients and oxygen. Anatomically, the aorta is divided into three key segments: the ascending aorta, the aortic arch, and the descending aorta, each of which contributes to systemic circulation.

(a) Aortic stenosis :is a pathological condition characterized by the narrowing of the aortic valve, which restricts blood flow from the left ventricle into the aorta. It is frequently observed in older individuals and is commonly attributed to valvular calcification or degenerative processes. Clinically, it presents with symptoms such as chest pain, dyspnea, fatigue, and syncope. Accurate evaluation of this condition is greatly enhanced through the analysis of hemodynamic flow parameters, which are instrumental in identifying the mechanical consequences of the stenosis and its potential role in the progression of cardiovascular disease.

(b)Aortic dissection :, in contrast, is an acute and life-threatening condition involving a tear in the inner layer of the aortic wall. This tear allows blood to enter between the layers of the vessel wall, resulting in the formation of a false lumen and the possible separation of the arterial wall layers. It typically presents with a sudden onset of intense chest or back pain and requires immediate medical intervention due to its high risk of fatal complications.

II.4.2 Coronary Arteries

The coronary arteries, depicted in Figure 1 (e), are fundamental components of the cardiovascular system, tasked with supplying oxygenated blood to the myocardium. Originating from the aorta, these arteries encircle the heart and branch extensively to form a vascular network vital for maintaining cardiac function. Pathological alterations in the coronary arteries can result in myocardial ischemia, a condition characterized by insufficient perfusion of the heart muscle. If left untreated, chronic ischemia and its associated complications may lead to progressive deterioration of cardiac contractility, thereby increasing the risk of severe cardiovascular events. Consequently, early diagnosis and timely therapeutic intervention are essential to mitigating the potentially fatal consequences of coronary artery-related diseases.

(a)Coronary Artery Disease (CAD): CAD is the most prevalent form of heart disease and is caused by atherosclerotic plaque buildup that narrows or obstructs the coronary arteries. This occlusion impairs myocardial perfusion, manifesting clinically as angina pectoris (chest pain or discomfort) and, in advanced stages, myocardial infarction (MI), a condition where part of the heart muscle undergoes necrosis due to prolonged ischemia. Advanced CAD often necessitates invasive interventions such as Percutaneous Coronary Intervention (PCI) or coronary angioplasty, procedures aimed at mechanically dilating stenotic arteries and frequently involving stent placement to maintain arterial patency. In cases with extensive or complex multivessel disease, Coronary Artery Bypass Grafting (CABG) may be indicated, wherein grafts from other vessels are used to reroute blood flow around blocked arteries. The prompt and effective management of CAD remains critical for improving patient outcomes. Key research challenges persist in the accurate assessment, risk stratification, and personalized treatment planning of this condition.

(b)Coronary Microvascular Disease (CMVD): CMVD refers to pathological changes in the microvasculature of the coronary circulation, which may lead to ischemic symptoms in the absence of significant epicardial artery stenosis. This condition affects the heart's small vessels, impairing microcirculatory flow and resulting in symptoms such as chest discomfort and dyspnea, although it may also present asymptomatically. Unlike obstructive CAD, which is detectable via conventional coronary angiography, CMVD eludes such imaging modalities due to its impact on vessels below the resolution threshold. Thus, alternative diagnostic techniques, including advanced imaging and physiological testing, are essential for the identification and management of this elusive but clinically significant condition.

II.5 Clinical characteristics of Atrial Fibrillation: exploring its types and symptoms

Arrhythmia refers to a group of cardiac disorders characterized by abnormalities in heart rhythm, which can manifest in a variety of clinical contexts. Based on heart rate deviations, arrhythmias are broadly classified into two categories :

1.Tachycardia : This term denotes an abnormally rapid heart rate, typically defined as exceeding 100 beats per minute in adults. Tachycardia may arise from both physiological and pathological conditions and can compromise effective cardiac output if sustained.

2.Bradycardia: In contrast, bradycardia describes an unusually slow heart rate, generally defined as fewer than 60 beats per minute. While it may be asymptomatic in certain individuals, particularly athletes, it can also signal underlying conduction system disorders or other pathological states.

To assess and diagnose arrhythmic conditions, electrocardiography (ECG) remains the standard non-invasive diagnostic tool, enabling clinicians to evaluate the electrical activity and rhythm of the heart with precision[47].

Atrial fibrillation (AF) is the most prevalent type of cardiac arrhythmia, characterized by irregular and often rapid atrial electrical activity that disrupts coordinated heart contractions [48].

Prolonged electrocardiogram (ECG) monitoring is a widely adopted approach for the early detection of AF, enabling timely clinical intervention and risk mitigation [Sensors].

However, motion artifacts (MAs) present in ECG recordings can substantially distort the signal morphology, potentially impairing the accurate identification of arrhythmic patterns and delaying diagnosis. Given the association of AF with increased risks of stroke and other cardiovascular complications, early and accurate detection is critical for effective patient management and therapeutic decision-making [49].

Atrial Fibrillation (AF) is a common and clinically significant cardiac arrhythmia associated with elevated risks of stroke, heart failure, and cardiovascular mortality [46]. It is characterized by the rapid and disorganized electrical activity in the atria, the upper chambers of the heart, which leads to inefficient atrial contraction and suboptimal blood ejection, thereby predisposing patients to thrombus formation and subsequent embolic events [46]. The pathophysiology of AF is complex and influenced by both physiological and pathological conditions, including exercise-induced autonomic modulation.
Evidence suggests that high-intensity, short-duration exercise may trigger excessive sympathetic nervous system activation, whereas prolonged endurance exercise tends to enhance parasympathetic tone. These alterations in autonomic balance can lead to shortened action potential duration and effective refractory period in atrial myocytes, promoting increased automaticity and atrial ectopy, and ultimately facilitating AF onset. Although age is a significant risk factor, and the condition is more prevalent among the elderly, AF can also occur in younger individuals without pre-existing cardiac pathology, particularly those exposed to extreme physical stress [50]. Clinically, AF is associated with a fivefold increase in the risk of ischemic stroke and a threefold increase in the likelihood of developing heart failure, underscoring the importance of early detection and intervention.

Atrial Fibrillation (AF) can be clinically categorized into three subtypes based on the duration and persistence of arrhythmic episodes: paroxysmal, persistent, and permanent AF.

Paroxysmal AF refers to self-terminating episodes that last seven days or less, typically resolving spontaneously.

Persistent AF extends beyond seven days and requires therapeutic intervention, such as pharmacological or electrical cardioversion, to restore normal sinus rhythm.

Permanent AF is characterized by a sustained arrhythmic state in which rhythm control strategies are no longer pursued, either due to therapeutic failure or clinical decision-making.

Importantly, despite differences in episode duration and management strategies, all three forms of AF carry a comparable risk of thromboembolic complications, including stroke. Therefore, accurate and timely detection of AF episodes, especially transient or asymptomatic ones, is critical. Early identification facilitates appropriate anticoagulant therapy, which is central to reducing the risk of adverse cardiovascular outcomes.

Normal ECG signals are composed of several distinct waves, including the P wave, QRS complex, and T wave, each reflecting different aspects of the cardiac electrical activity. The statistical and morphological features of these waves are crucial indicators of heart health and can provide valuable insights into various cardiovascular conditions. For instance, the absence of P waves and the presence of an irregular ventricular rate in ECG signals are hallmark signs that may suggest the presence of atrial fibrillation (AF). These abnormalities can be pivotal for early diagnosis and management of AF, underscoring the significance of careful wave analysis in clinical ECG interpretation [51].

Changes in specific ECG features over time can serve as indicators of underlying heart disease. As depicted in the figureII.2, a complete heartbeat in the ECG corresponds to a full cardiac cycle. In a typical ECG cycle, the characteristic waveforms include the P wave, QRS complex (comprising the Q wave, R wave, and S wave), T wave, and U wave.

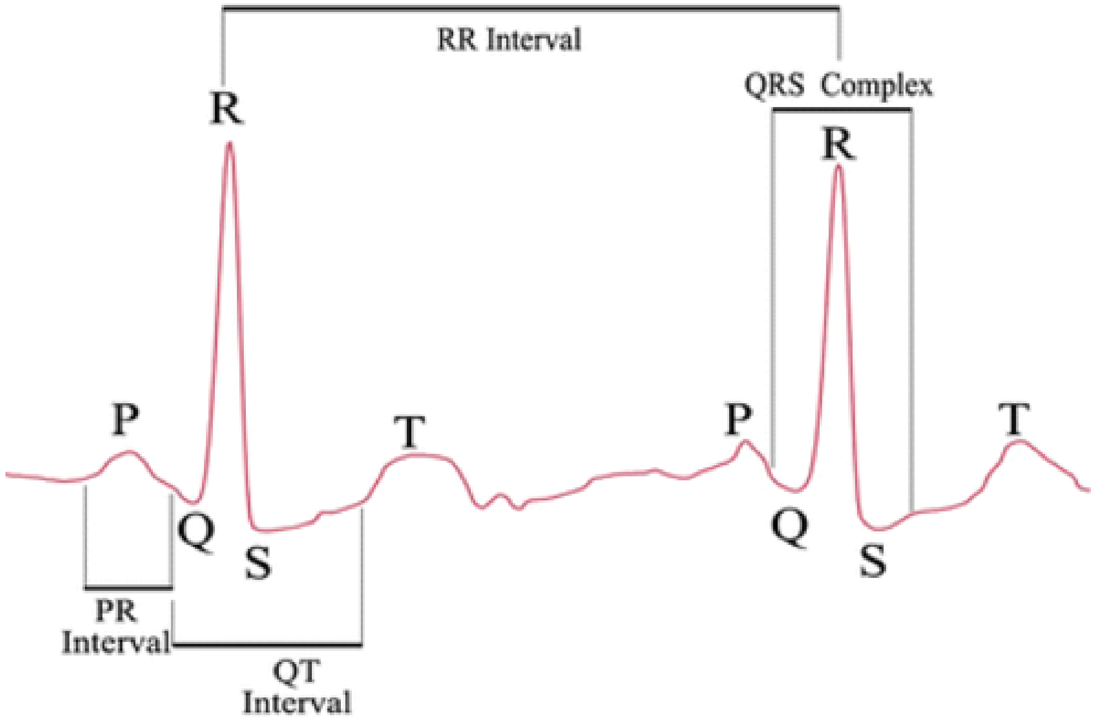


Figure II.2: ECG characteristics [9].

Atrial fibrillation (AF) is commonly diagnosed using electrocardiography (ECG) in clinical settings, with two prominent manifestations observed in the ECG signal. First, in AF, the RR interval becomes completely irregular, in contrast to the regular and consistent RR intervals seen in normal ECG signals. Although the RR interval feature is relatively straightforward to extract and the associated algorithms for its analysis are well-established, it is important to note that other types of arrhythmias may also present with irregular RR intervals, which necessitate more comprehensive analysis to differentiate between different arrhythmia types.

II.6 Automated Atrial Fibrillation (AF) detection-based AI paradigms

Atrial Fibrillation (AF) has emerged as a significant global health issue, yet the absence of targeted prevention strategies highlights the pressing need for early, widespread public health interventions. The manual interpretation of electrocardiograms (ECGs) for the diagnosis of AF remains a time-consuming process, prone to observer variability and errors, often influenced by the expertise of the cardiac specialist interpreting the results [46] [52]. Early detection of AF is critical to mitigate complications and reduce the risk of premature mortality. Timely diagnosis enables the initiation of appropriate preventive treatments, such as anticoagulation therapy, which is essential for preventing cardioembolic strokes.

In recent years, deep learning (DL) approaches have become instrumental in advancing the early detection and continuous monitoring of atrial fibrillation (AF) [49]. Computer-aided diagnosis (CAD) systems, leveraging artificial intelligence (AI) techniques, have been extensively developed to support the automated identification of AF [50]. A variety of machine learning and deep learning algorithms have been proposed for this purpose. To improve the accuracy and computational efficiency of AF detection, researchers have introduced ECG signal classification models based on convolutional neural networks (CNNs), as well as hybrid architectures that integrate CNNs with long short-term memory (LSTM) networks. These models are capable of efficiently extracting relevant features and capturing complex temporal dependencies within ECG signals, thereby enhancing AF detection performance.

Numerous automated algorithms have been developed to analyze the surface characteristics of Electrocardiogram (ECG) signals, particularly in the context of arrhythmia detection [46]. Many of these techniques focus on two primary alterations that atrial fibrillation (AF) induces in ECG signals. First, AF is marked by rapid atrial activation, with rates ranging between 240 and 540 beats per minute. This rapid activity results in an irregular and accelerated ventricular response, as the atrioventricular (AV) node receives continuous electrical impulses. Such irregularity leads to a loss of the consistent R-R interval pattern typically observed in Normal Sinus Rhythm (NSR). Second, in contrast to the regular and well-defined P-waves seen in NSR, indicative of orderly atrial depolarization, AF manifests through a succession of low-amplitude, morphologically variable fibrillatory waves (f-waves), reflecting the chaotic atrial activity.

II.7 Problematic

Atrial fibrillation (AF) is a prevalent and clinically significant arrhythmia associated with substantial morbidity. Early identification of individuals at heightened risk for AF is of paramount importance in clinical practice. Proactive risk stratification allows for targeted lifestyle and behavioral interventions that may reduce the incidence of AF. Moreover, cardiac rhythm monitoring in at-risk populations can facilitate the detection of previously undiagnosed AF, thereby providing an opportunity to implement stroke prevention strategies such as anticoagulation therapy [53].

1- In routine clinical practice, electrocardiogram (ECG) screening is commonly employed by cardiologists to detect cardiac abnormalities and inform appropriate treatment strategies. However, this process often demands substantial manual effort and costly medical resources. With the rapidly aging global population, the incidence of cardiovascular diseases (CVDs) is projected to rise significantly. This trend underscores the urgent need for efficient, accurate, and cost-effective automated ECG analysis systems to support large-scale screening and early diagnosis [51].

2- Atrial Fibrillation (AF) affects approximately 2major risk factor for embolic stroke. Notably, previous studies have reported an average inter-physician agreement rate of only 72% in the diagnosis of AF, highlighting the variability and challenges associated with manual interpretation [54].

3- To ensure consistency and reliability in Electrocardiogram (ECG) analysis, measurement conditions must be standardized across patients, and accurate annotation of ECG signal samples is essential, typically requiring specialized facilities and substantial expert input from cardiologists. Given these constraints, publicly available ECG databases currently serve as primary resources for deep learning (DL)-based arrhythmia classification and are instrumental in advancing research in this domain. Nonetheless, the manifestation of arrhythmias in ECG signals can differ significantly across individuals. Thus, leveraging a variety of ECG datasets allows DL models to encounter a broader spectrum of patterns, which can enhance their generalization capability and improve inference accuracy in real-world clinical settings [51].

4- In the PhysioNet Computing in Cardiology Challenge 2020, participants were granted access to seven publicly available ECG datasets. However, these databases exhibit considerable variability in terms of lead configuration, signal duration, measurement conditions, and patient demographic distributions, factors that must be carefully considered rather than overlooked [51]. A notable limitation of current arrhythmia-related ECG databases is the significant class imbalance, with normal ECG recordings vastly outnumbering pathological cases. While techniques such as data augmentation are commonly employed to mitigate this issue, the most effective solution remains the collection of additional pathological ECG data. However, obtaining such data is inherently challenging, as it requires access to patients with specific cardiac conditions. Consequently, dataset imbalance remains a persistent and fundamental challenge in automated ECG classification research [51].

5- Electrocardiogram (ECG) signals are typically recorded at high sampling rates, resulting in large volumes of data that pose significant computational and storage challenges. The processing and analysis of such high-resolution signals often require substantial memory resources, with a minimum of 16 GB RAM commonly necessary to ensure efficient handling and real-time performance. These hardware demands highlight an important computational bottleneck in the deployment of ECG-based diagnostic systems, particularly in resource-constrained environments.

6- Electrocardiogram (ECG) signals are frequently susceptible to various sources of noise, including motion artifacts from patient movement, electromagnetic interference, and improper electrode placement. These disturbances can significantly compromise signal quality, thereby hindering accurate feature extraction and classification. Consequently, the development and integration of robust filtering and denoising algorithms are essential to ensure the reliability and precision of ECG-based diagnostic systems.

7- Empirical evidence suggests that atrial fibrillation (AF) screening can be cost-effective, particularly by facilitating the early identification of individuals with a high AF burden who may benefit from timely anticoagulation therapy and initiation of rhythm or rate control strategies. Such interventions have been shown to reduce postoperative hospital stays. Nevertheless, the paroxysmal and frequently asymptomatic nature of AF poses significant challenges for conventional diagnostic methods. Current screening techniques often prove insufficient, as effective AF detection requires extensive and labor-intensive ECG monitoring, which is further complicated by the large volume of ECG data requiring expert review [54] .

8- The diagnosis of atrial fibrillation (AF) may be overlooked when ECG interpreters are faced with a high volume of recordings, as the sheer amount of data can overwhelm the diagnostic process.

9- The diagnosis of atrial fibrillation (AF) necessitates electrocardiographic (ECG) evidence of the arrhythmia on at least one lead. Paroxysmal AF is often overlooked during routine office ECG screenings. However, extended-duration portable ambulatory ECG monitoring, such as 24-hour Holter recording, enhances the likelihood of detecting AF. Despite this, the substantial volume of ECG data generated by such monitoring poses a significant challenge, as it requires extensive and time-consuming analysis [51].

II.8 Related works on Automated Detection of Atrial Fibrillation (AF)

Globally, various approaches for the automatic detection of arrhythmias, particularly Atrial Fibrillation (AF), have been developed to diagnose patients as depicted in the table II.1. Recent advancements have led to the creation of several machine learning (ML) and deep learning (DL)-based classifiers for the classification and detection of cardiac conditions from ECG signals. For a comprehensive review of the current progress in diagnosing atrial fibrillation through wearable devices and artificial intelligence, readers are referred to [cccc].

Table II.1: Several approaches for the automatic detection of Atrial Fibrillation (AF).

Ref	**Type**	**Methodology**	**Dataset**	**Results**
[55]	Normal and atrial fibrillation	A novel DL model that leverages **ConvMixer** and Transformer architecture, combining convolutional neural networks and attention mechanism to extract both local and global features from ECG data.	**PhysioNet /CinC 2017**	**Acc** = 91.66%
[56]	**AF prediction**	A DL model **MVPNNet** combines wavelet-based feature extraction and a deep learning classifier for detecting the approaching of AF onset by analyzing the template and frequency in P-wave segments.	/	**Acc** = 89%
[57]	Normal, atrial fibrillation, atrial flutter and **AV junctional rhythm**	A novel hybrid neural model utilizing ECG features initially extracted via a Convolutional Neural Network (CNN) and are input to a Long Short-Term Memory (LSTM) model for temporal dynamics memorization.	**MIT-BIH Atrial Fibrillation**	**Sensitivity** = 97.87%, **Specificity** = 99.29%

Ref	Type	Methodology	Dataset	Results
[58]	Normal and atrial fibrillation	An end-to-end model combining the Convolutional- and Recurrent-Neural Networks (CNN and RNN) was proposed to extract high level features from segments of RR intervals (RRIs)	**MITDB**	**Acc** = 89.3% **Sensitivity** = 98.89% **Specificity** = 96.5%
[59]	Non-Atrial Fibrillation (N-AF), Atrial Fibrillation (AF) and Normal Sinus Rhythm (NSR)	A novel AF detection model has been proposed: a conglomerate parallel structure of Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) framework which can deepen the understanding of features and classification.	**MIT-BIH**	**Acc** = 99.6% **Sensitivity** = 98.64% **Specificity** = 99.01%
[60]	/	Atrial fibrillation detection based on multi-feature extraction and convolutional neural network for processing ECG signals with SVM classification.	/	**Acc** = 98.92% **Sensitivity** = 97.19% **Specificity** = 97.04%
[61]	Normal and atrial fibrillation	The proposed method constructed a novel one-dimensional deep densely connected neural network (DDNN) to detect AF.	16.557 ECG recordings collected from multiple hospitals	**Acc** = 99.35 % **Sensitivity** = 99.19% **Specificity** = 99.44%

Ref	Type	Methodology	Dataset	Results
[62]	Normal and atrial fibrillation	An XAI-enabled atrial fibrillation diagnosis model based on a convolutional neural network (CNN) algorithm was proposed, along with Holter electrocardiogram monitoring data and the gradient-weighted class activation mapping (Grad-CAM) method.	57.273 electrocardiogra data	**Acc** = 95.3 % **Sensitivity** = 97.1% **Specificity** = 94.5%

Recent studies confirm the promising potential of artificial intelligence in predicting Atrial Fibrillation (AF). However, the specific ECG features that influence AF risk predictions made by ECG-based AI models remain unclear. Understanding these features is essential for evaluating potential biases and enhancing the confidence of clinicians in these models. Additionally, many of the existing models are proprietary and have not undergone thorough external validation.

II.9 Conclusion

Recent advancements in mobile technology, particularly in hardware and computational capabilities, have paved the way for the development of cost-effective, widely accessible, and accurate medical devices. These innovations hold the potential to mitigate the shortage of healthcare resources and help reduce healthcare expenditures. In the subsequent chapter, we explore the development of an IoT-enabled ECG monitoring device designed to analyze ECG signals for the early detection of atrial fibrillation.

CHAPTER III

IOT-BASED SYSTEM DESIGN FOR EARLY ATRIAL FIBRILLATION (AF) DETECTION

III.1 Introduction

The continuous rise in heart disease has created an urgent need to develop smart systems capable of early detection of heart attacks. With the advancement of Internet of Things (IoT) technologies, it has become possible to design portable and low-cost solutions that allow real-time monitoring of heart health outside medical institutions. This chapter presents the design of an intelligent IoT-based system aimed at collecting and analyzing electrocardiogram (ECG) data in real time, thereby enhancing the chances of early intervention and reducing the health risks associated with heart disease.

III.2 Overview of the IoT Architecture

The IoT-based ECG monitoring system is structured in a layered architecture that enables real-time data acquisition, processing, transmission, and intelligent analysis. This architecture is generally composed of four main layers:

- Perception Layer (Sensing Layer): This layer includes physical sensors such as the AD8232 ECG sensor, responsible for acquiring biopotential signals from the patient. These signals reflect the electrical activity of the heart.
- Network Layer (Communication Layer): The ESP8266 microcontroller processes and digitizes the analog ECG signals and uses its built-in Wi-Fi module to transmit the data wirelessly. The communication protocol used (HTTP) ensures reliable and low-latency data delivery to a cloud server or local gateway.
- Processing Layer (Data Management Layer): The server or cloud infrastructure stores, organizes, and processes the incoming ECG data. This layer often includes databases, APIs, and pre-processing algorithms to clean and prepare data for further analysis.
- Application Layer (AI and Visualization): The processed data is analyzed by AI models for real-time arrhythmia detection. The results are then displayed through a user-friendly dashboard accessible to healthcare providers, allowing for remote diagnosis and alerting in case of abnormalities.

[63]

This layered architecture ensures modularity, scalability, and efficiency, enabling continuous and intelligent health monitoring in real-world IoT healthcare deployments.

III.3 Hardware Components Description

The proposed system for early heart attack detection consists of a set of electronic components carefully selected to achieve a balance between accuracy, low power consumption, and ease of use. A detailed description of these components is presented below :

III.3.1 Arduino ESP8266

The Arduino ESP8266 is a widely used open-source microcontroller, especially in IoT applications, due to its built-in support for Wi-Fi and Bluetooth connectivity. It features both digital and analog input/output pins, allowing integration with various electronic components or expansion boards. Programming is performed through the Arduino IDE, which offers a user-friendly environment for development. One of its key advantages is wireless communication capability, making it ideal for implementing smart and connected systems[10],The following is an illustrative image III.1 of this microcontroller.

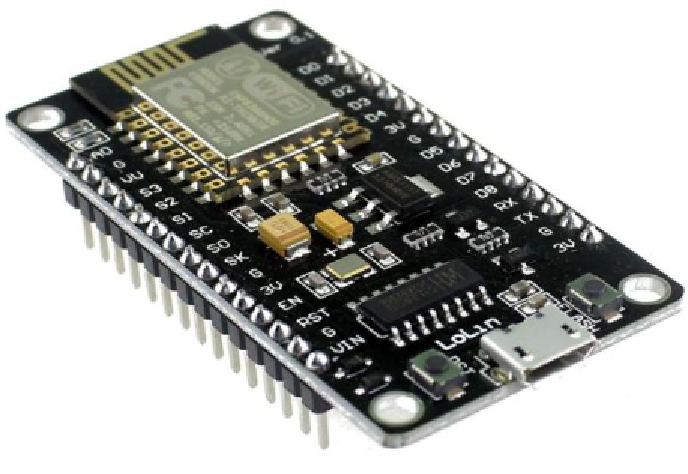


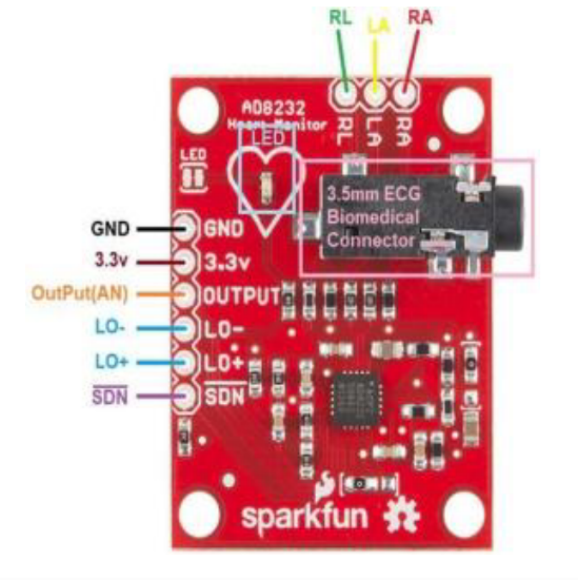
Figure III.1: Pin diagram of the Arduino NodeMCU [10]

III.3.2 ECG Sensor(AD8232)

The AD8232 is specifically designed for conditioning bio-potential signals such as ECG, enabling the extraction of clean signals even in noisy environments caused by motion or poor electrode contact. It incorporates amplification and filtering stages that help minimize noise and enhance signal quality.

The device uses a second order high-pass filter to eliminate motion artifacts and can be integrated with an instrumentation amplifier to achieve high gain in a single stage. One of its key features is the fast restore function, which allows the device to quickly recover from signal interruptions—such as lead disconnections and resume accurate measurements shortly after reconnection.

Thanks to its robust design, the AD8232 is well-suited for applications that require both precision and responsiveness. It operates over a wide temperature range from -40°C to 85°C[10].As illustrated in the figureIII.3.4.



(A)

(B)

Figure III.2: AD8232 ECG sensor device. (A) Components. (B) Pin diagram[10]

III.3.3 Battery

We selected a 3.7V Lithium-Polymer (Li-Po) battery as the power source for the proposed system due to its advantageous features for portable and wearable applications.

It provides high energy density, lightweight design, and stable voltage output, allowing the system to operate for moderate durations ranging from 4 to 6 hours depending on the battery's capacity. These features make it an ideal option for delivering reliable and sustainable power in continuous ECG monitoring systems [64].As illustrated in the figure III.3.3.

Figure III.3: Battery 3.7v [65]

III.3.4 AMS1117-3.3V Voltage Regulator

The AMS1117-3.3V is a low-dropout (LDO) linear voltage regulator designed to provide a stable 3.3V output from a higher input voltage source of up to 15V. It can supply output currents of up to 1 ampere, with a typical dropout voltage of about 1.1V under full load.

This regulator comes in a compact SOT-223 package and integrates essential protection features such as thermal shutdown and overcurrent protection, making it highly suitable for embedded systems, sensor modules, microcontroller circuits, and other applications requiring precise voltage regulation. **Key Features:**

- Fixed output voltage: 3.3V
- Output current up to 1A
- Low dropout voltage (1.1V)

- Compact design for embedded applications
- Built-in thermal and short-circuit protection

[66]As illustrated in the figure III.3.4.

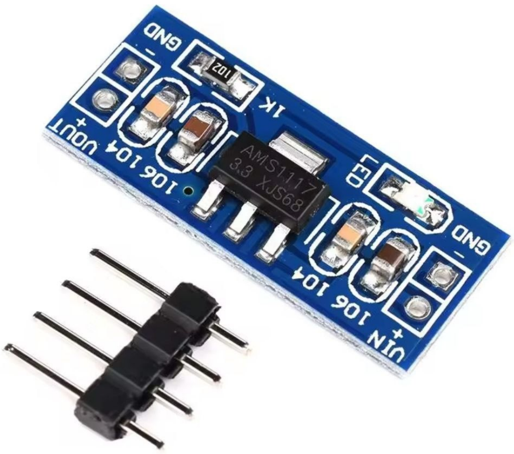


Figure III.4: AMS1117 3.3V Voltage Regulator Module[11]

III.3.5 Circuit Diagram

In this project, a fully integrated electronic system was designed to monitor the electrical activity of the heart (Electrocardiography - ECG), utilizing the **ECG Sensor(AD8232)** medical-grade sensor and the compact **Arduino ESP8266**. This system is responsible for acquiring vital cardiac signals and analyzing them in real-time. It is powered by a **portable 3.7V 1100mAh lithium polymer battery**, with voltage regulation handled by the **AMS1117-3.3V voltage regulator**, ensuring a stable and safe current supply to all electronic components in accordance with the operating requirements of the ESP8266 and the sensor.

The AD8232 sensor requires three electrodes to be placed on the user's body in specific locations to accurately capture the cardiac bio-signals: one on the right arm (RA), another on the left arm (LA), and the third on the right leg (RL), which serves as the ground reference. The AD8232 unit amplifies and filters the heart's electrical signals, then outputs the analog signal to **ESP8266** for subsequent processing.

The connections between the AD8232 module and the NodeMCU are configured as follows:

- **3.3V to 3.3V:** to power the sensor.
- **GND to GND:** to provide a common electrical ground.
- **OUTPUT to A0:** to transmit the analog signal from the sensor to the microcontroller.
- **LO+ and LO to D5 and D6:** to detect electrode disconnection (optional feature).
- **SDN:** not used in this design; optionally connected to GND to keep the sensor permanently enabled.

The system is powered by a lithium polymer battery, and the **AMS1117-3.3V voltage regulator** is used to step down the voltage to a stable 3.3V. This ensures safe and reliable operation of both the **ESP8266 board** and the **AD8232 sensor**, protecting them from potential overvoltage damage.

Thanks to this architecture, the system can wirelessly transmit vital ECG data via Wi-Fi to an external server or a dedicated application, enabling remote, real-time cardiac monitoring. This solution provides an energy-efficient, cost-effective, and portable approach well-suited for smart healthcare applications.

As illustrated in the figure III.4.1 below:

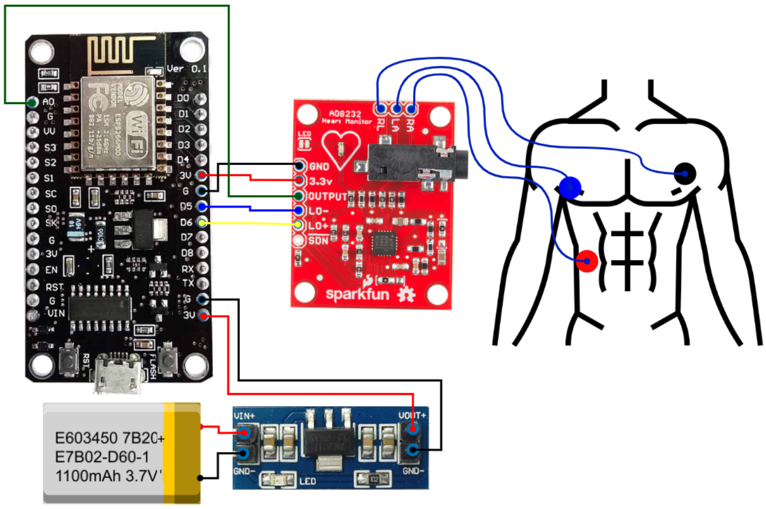


Figure III.5: Circuit diagram showing the connection between the AD8232 ECG sensor, NodeMCU ESP8266, and AMS1117-3.3V voltage regulator powered by a 3.7V Li-Po battery

III.4 Sensor Data Acquisition and Signal Preprocessing

III.4.1 Sensor Data Acquisition

The electrical signals generated by cardiac activity (Electrocardiogram - ECG) are acquired using the AD8232 sensor, a dedicated integrated circuit designed for biopotential signal acquisition. The sensor detects subtle electrical changes on the skin surface caused by heartbeats through three electrodes placed on the patient's body in accordance with Einthoven's triangle configuration (RA – Right Arm, LA – Left Arm, RL – Right Leg). These electrodes measure voltage differences corresponding to the cardiac cycle and output a continuous analog ECG signal[67] .

This analog signal is then passed to the ESP8266 microcontroller, which converts the signal into a digital format using its built-in Analog-to-Digital Converter (ADC). A sampling rate of approximately 300 Hz is used, providing sufficient resolution to capture essential cardiac signal components such as P waves, QRS complex, and T waves[67] .

Once digitized, the ESP8266 uses its integrated Wi-Fi module to wirelessly transmit the ECG data to the server in real-time. This transmission method enables continuous remote cardiac monitoring, making the system suitable for portable healthcare applications and IoT-based health systems[67]As illustrated in the figure III.4.1. .

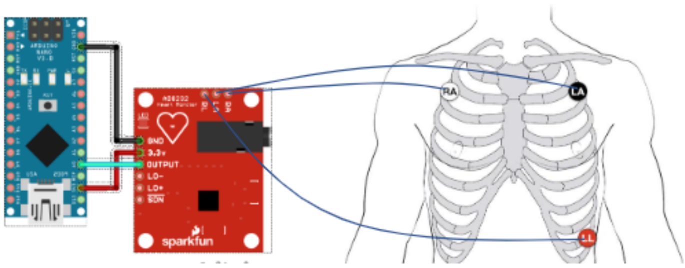


Figure III.6: Sensor Data Acquisition[68]

III.4.2 Signal Preprocessing

Due to the highly sensitive nature of ECG signals, the system encountered significant noise levels in the raw signal, primarily caused by motion artifacts, electromagnetic interference (EMI), and voltage mismatches between components. To ensure clean signal acquisition and reliable transmission, the following preprocessing steps were implemented:

- Voltage Regulation: A voltage divider circuit was used to convert the AD8232 output signal from 5V to 3.3V, matching the ESP8266 analog input range and reducing voltage-induced distortion.
- Denoising Using Wavelet Transform: Following the initial analog filtering provided by the AD8232 circuit, digital signal processing was performed using the Wavelet Transform technique. This method is considered one of the most effective tools in biomedical signal processing, as it enables multi-level analysis of the signal in both time and frequency domains simultaneously. This capability allows for the identification of fine-grained details within the ECG signal. The Wavelet Transform was chosen for its effectiveness in removing noise across multiple frequency bands without affecting key physiological components such as the QRS complex, and the P and T waves. Furthermore, wavelets offer a high capacity to separate clinically significant features from background noise, thereby enhancing the overall signal quality and providing a reliable foundation for ECG analysis.. [69].

III.5 Communication Protocol and Data Transmission

This ECG monitoring system is built upon an integrated Internet of Things (IoT) architecture designed to enable efficient and secure transmission of biomedical data. The process begins with the ESP8266 microcontroller, which reads the analog signal from the AD8232 sensor and converts it into a digital format using its built-in Analog-to-Digital Converter (ADC). The data is then transmitted over Wi-Fi using the HTTP protocol to a server developed with the FastAPI framework.

The server processes the incoming ECG signals by applying a machine learning model based on the Support Vector Machine (SVM) algorithm, enhanced with a pre-trained feature extractor implemented using TensorFlow. After classification, both the diagnostic result and the original signal are sent to Firebase Firestore, along with long-term storage in Firebase Storage.

In the final stage, a cross-platform Flutter application retrieves the data from Firebase and displays it through an interactive user interface, allowing physicians to access and analyze the results in real time. The system is powered by a 3.7V Lithium-Polymer (Li-

Po) battery, supported by a voltage regulator that steps down from 5V to 3.3V, ensuring stable operation of all electronic components.The following Figure III.7 illustrates the ECG Data Transmission via Wi-Fi to Central Server for Remote Monitoring .

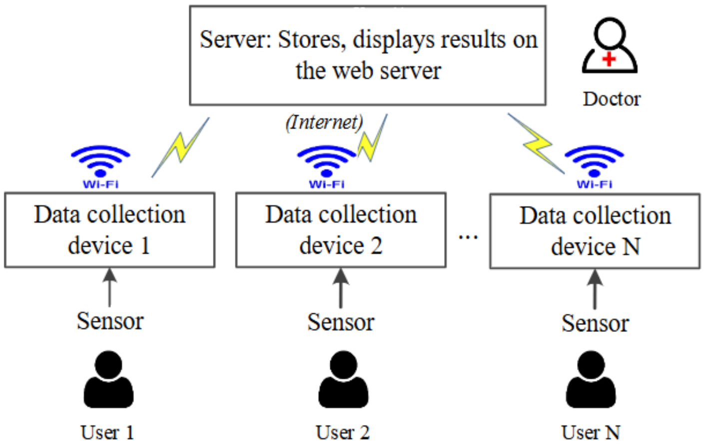


Figure III.7: ECG Data Transmission via Wi-Fi to Central Server for Remote Monitoring[12]

III.6 Integration with AI Prediction Model

After the preprocessing of the ECG signal and its transmission, the system is integrated with an artificial intelligence-based prediction model to detect and classify bothatrial fibrillation (AF) and normal conditions . This integration ensures real-time decision support and enhances the system's ability to assist in remote diagnosis. The process includes the following components:

- Input Vector Construction: After noise removal, ECG signals are segmented and transformed into feature vectors using indicators from both the time and frequency domains, such as wavelet coefficients and RR intervals, to extract the most relevant cardiac features.
- Model Deployment: A pre-trained Support Vector Machine (SVM) model is deployed to classify ECG signals into two categories: atrial fibrillation (AF) and normal (N). The model is executed on a remote server with sufficient computational resources to ensure accurate and efficient real-time processing.
- Prediction and Feedback: The model generates a prediction of the cardiac condition, which is stored and made accessible through a web-based dashboard for medical

personnel. In the event of AF detection, an immediate alert is sent to the physician via a dedicated mobile application, enabling timely intervention.

This AI-powered integration bridges the gap between biosignal sensing and intelligent diagnosis, offering a scalable solution that supports continuous and smart health monitoring, and facilitates remote medical care.

III.7 Conclusion

In conclusion of this chapter,the proposed intelligent system represents an effective step toward empowering individuals to proactively monitor their heart health, leveraging Internet of Things (IoT) technologies to provide accurate, low-cost, and user-friendly solutions. Such systems not only contribute to the early detection of heart attacks but also enhance the quality of preventive healthcare beyond hospital settings.

CHAPTER IV

EXPERIMENTAL DESIGN AND MODEL DEVELOPMENT FOR ATRIAL FIBRILLATION (AF) DETECTION

IV.1 Introduction

In this chapter, we present the proposed methodology to address the problem discussed in Chapter Two, which involves developing an intelligent approach for the diagnosis of Atrial Fibrillation (AF). This methodology is based on the integration of artificial intelligence techniques, particularly machine learning and deep learning, as previously discussed. Advanced processing of electrocardiogram (ECG) signals was adopted, in addition to the integration of Internet of Things (IoT) technologies to enable real-time diagnosis and continuous health monitoring.

IV.2 Methodology

Developing models capable of automatically detecting the onset and duration of atrial fibrillation (AF) episodes holds significant value in terms of diagnosis and prediction. Empirical evidence has demonstrated that deep learning algorithms, when trained on large-scale electrocardiogram (ECG) datasets, can accurately identify AF patterns often achieving performance comparable to or even surpassing that of expert physicians [45]. Integrating advanced signal processing techniques with machine learning approaches in AF detection systems has shown great promise in reducing diagnostic bias and human error, thereby enhancing the accuracy and efficiency of AF detection [50]. In this context, AI models based on ECG have been proposed as effective tools for AF screening, particularly for mitigating the disproportionate risk burden among patients with heart failure or stroke, while simultaneously aiming to improve healthcare quality and reduce associated costs.

The design of deep learning models plays a pivotal role in the effectiveness of ECG-based arrhythmia classification systems [51]. These models typically consist of multiple hierarchical layers, each acting as a feature extractor capable of progressively and abstractly capturing the signal's distinctive characteristics. Leveraging this architecture, hybrid deep learning frameworks have been developed by combining different types of neural networks based on their intrinsic strengths. For example, convolutional neural networks (CNNs), such as ResNet, are employed to extract spatial features, while recurrent neural networks (RNNs), especially long short-term memory (LSTM) units, are used to model temporal dependencies within ECG signals. In this configuration, CNN layers are usually placed at the initial stages to extract deep spatial features, which are then processed by LSTM layers to capture sequential patterns, enhancing arrhythmia detection performance.

The proposed model architecture integrates one-dimensional convolutional layers and recurrent neural networks in a unified framework to capture both spatial and temporal characteristics in ECG signals. Initially, the model applies a series of 1D convolutional layers organized into residual blocks based on the ResNet design. Skip connections within these blocks maintain gradient stability and promote deep and efficient learning, while extracting local features from input sequences. Following the convolutional stage, stacked LSTM layers model the temporal dynamics of the extracted features, allowing the network to learn long-range dependencies necessary for interpreting evolving patterns in time-series data. The sequential output from the LSTM is subsequently processed through fully connected layers that compress the high-dimensional feature space, culminating in a softmax layer for probabilistic classification. Additionally, the model includes a feature extraction submodule that captures high-level representations prior to final classification. To enhance temporal sensitivity, several hand-crafted temporal features are integrated, such as mean heart rate (HR_Mean), standard deviation of RR intervals (HRV_SDNN), mean RR interval (RR_Interval_Mean), standard deviation of RR intervals (RR_Interval_Std), and average QRS complex duration (QRS_Duration). This hybrid ResNet-LSTM model is particularly well-suited for ECG-based time-series classification, where both local spatial patterns and extended temporal dependencies must be jointly modeled.

Accordingly, the proposed model is capable of capturing localized spatial features and long-term temporal dependencies within ECG signals. To complement temporal analysis, a set of frequency-domain features—clinically relevant indicators of autonomic nervous system activity—are also extracted. Specifically, we compute the power spectral density in the low-frequency band (LF: 0.04–0.15 Hz) and high-frequency band (HF: 0.15–0.4 Hz), referred to as LF_Power and HF_Power, respectively. In addition, the LF/HF ratio is derived as an indicator reflecting the balance between sympathetic and parasympathetic influences. When combined with deep-learned representations, these frequency-based features contribute to a more comprehensive characterization of heart rhythms, enhancing the model's ability to differentiate and detect arrhythmias.

After preprocessing and analyzing ECG data sourced from the PhysioNet database, machine learning algorithms were employed to build a robust classification model for detecting arrhythmias. To address class imbalance—particularly the underrepresentation of AF cases—Synthetic Minority Oversampling Technique (SMOTE) was applied only to the training set. This technique generates new minority class samples by interpolating between existing examples, thereby boosting AF representation while reducing the risk of overfitting often associated with simple random duplication strategies.

The emergence of Internet of Things (IoT) technologies offers transformative potential for early detection and continuous management of cardiovascular disorders, particularly arrhythmias. To deploy the proposed AF detection model in a real-world setting, an integrated monitoring system based on IoT architecture was developed, enabling continuous and secure monitoring of ECG signals. This system uses the ESP8266 microcontroller to read analog signals from the AD8232 sensor and convert them into digital form via its built-in ADC (Analog-to-Digital Converter). The digitized data is then transmitted over Wi-Fi using the HTTP protocol to a backend server developed with the FastAPI framework and hosted on the Railway platform under the name custom server.

The incoming raw ECG signal is first processed using wavelets to remove noise, then passed through a machine learning classifier based on a Support Vector Machine (SVM), which was trained on pre-extracted features (temporal, frequency-based, and deep features derived from the hybrid LSTM-ResNet model) to classify the signals and detect AF episodes. After classification, the diagnostic results along with the original signal are permanently stored in Firebase Firestore to ensure data preservation and future accessibility.

To provide an effective medical user interface, a cross-platform Flutter application was developed to retrieve and display data from Firebase interactively, allowing physicians to analyze diagnostic results in real time. The system is powered by a 3.7V lithium polymer battery, supported by a voltage regulator that steps it down to 3.3V to ensure stable operation of all electronic components. This integrated IoT-based architecture facilitates practical deployment of the intelligent model and supports remote heart monitoring and early intervention in case of arrhythmia detection. The system's continuous and multimodal monitoring capabilities enable early detection of cardiac anomalies, allowing immediate alerts to be sent to medical personnel upon suspected AF occurrence.

A schematic diagram illustrating the architecture of the proposed atrial fibrillation detection system will be provided below, highlighting the data flow between hardware and software components IV.3:

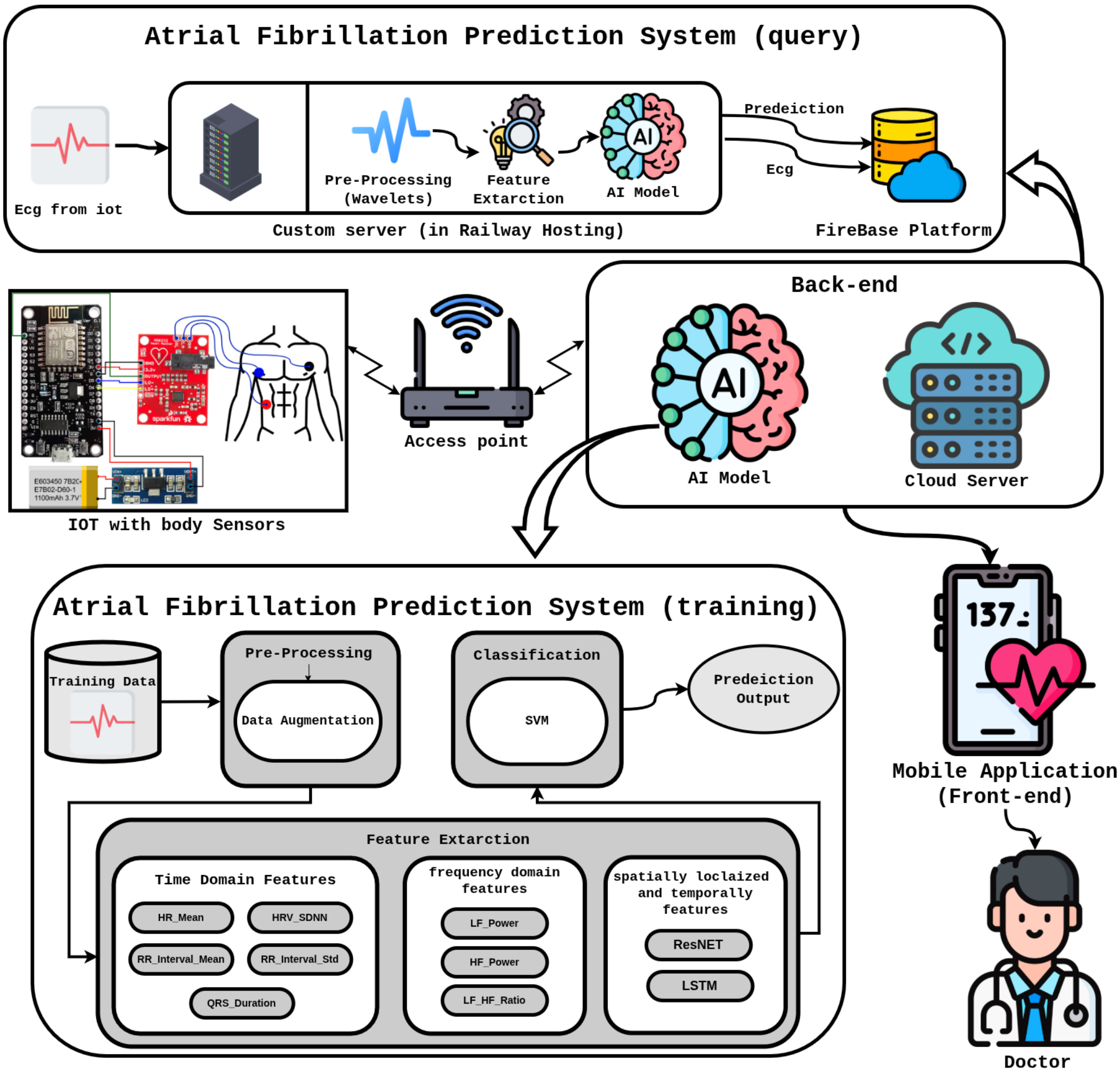


Figure IV.1: Proposed system architecture for atrial fibrillation detection using ECG sensor, artificial intelligence, and IoT-based deployment.

IV.3 Dataset Description and Preprocessing

IV.3.1 Dataset Description

In this project, we utilized electrocardiogram (ECG) signals obtained from the open-access PhysioNet database, a well-established and reputable source for biomedical signal analysis and artificial intelligence applications in healthcare. The ECG signals were recorded at a sampling rate of 300 Hz and underwent preprocessing through a band-pass filter integrated into the AliveCor device. This filtering process aimed to enhance the signal quality by minimizing noise before further analysis.

The dataset is provided in MATLAB V4 format, which is compliant with the WFDB

(WaveForm DataBase) standard. Each ECG recording consists of two files: a .mat file that contains the time-series ECG signal, and a .hea file that includes detailed information about the signal, such as the sampling rate and recording duration[70].

For the purposes of this project, we focused on two specific classes within the database: Normal Rhythm (N) and Atrial Fibrillation (AF). This binary classification approach was chosen to simplify the task and optimize the development of an efficient classification model. After thorough data inspection and filtering, we obtained a total of 5,050 samples belonging to the Normal Rhythm (N) class and 738 samples classified under Atrial Fibrillation (AF), yielding a total of 5,788 samples.

The dataset encompasses ECG recordings from individuals with diverse attributes, including variations in gender, age, and health status. This diversity contributes to the generalization capacity of the proposed AI model, enabling it to perform effectively across different patient populations. To ensure a robust evaluation of the model, the data was divided into two primary subsets: the Training set, which is used for training the model and optimizing its performance, and the Test set, which serves to evaluate the model's accuracy after training.

These datasets form the core of the training and evaluation process for the proposed AI model, with Figures IV.2 IV.3 illustrating representative examples of ECG waveforms from both Atrial Fibrillation and the Normal Rhythm classes. Additionally, preprocessing techniques were applied to address class imbalance, including the implementation of the SMOTE (Synthetic Minority Over-sampling Technique) approach, which is detailed in the following section.

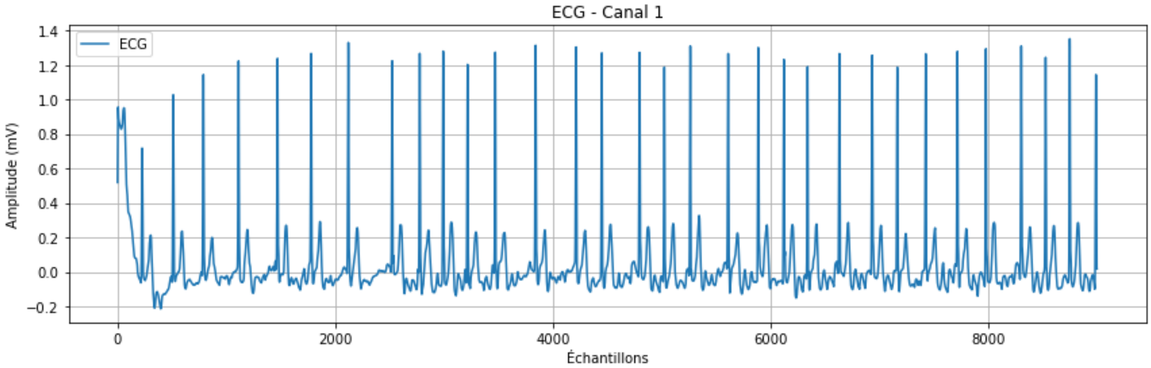


Figure IV.2: Example of an Atrial Fibrillation (AF) ECG

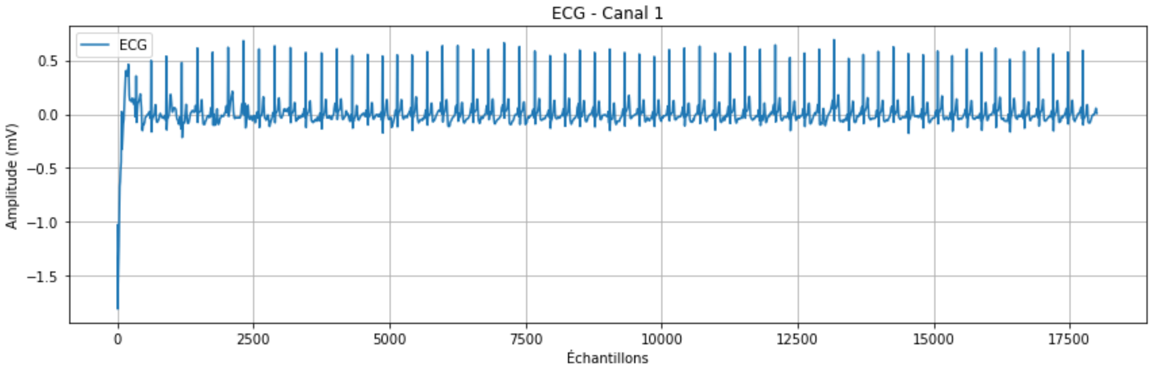


Figure IV.3: Example of a Normal (N) ECG

IV.3.2 Pre-processing

Following the extraction of relevant ECG signals from the PhysioNet database, a series of preprocessing techniques were applied to enhance the quality of the data and prepare it for training the proposed AI model.

The first step involved class balancing, as there was a notable imbalance in the number of samples between the Normal rhythm (N) and Atrial Fibrillation (AF) classes. To address this issue, the SMOTE (Synthetic Minority Over-sampling Technique) was applied. This technique generates synthetic examples of the minority class by interpolating between existing samples, which helps to prevent the model from becoming biased toward the majority class.

Additionally, feature scaling was performed using the StandardScaler technique, which standardizes each numeric feature by removing the mean and scaling to unit variance (mean = 0, standard deviation = 1). This normalization process improves the model's training stability and convergence speed, especially for algorithms that are sensitive to the scale of input features.

These preprocessing steps are essential for delivering balanced and standardized input data to the model, thereby directly contributing to improved accuracy and generalization performance.

IV.4 Feature Extraction

In this project, a hybrid approach was adopted that combines handcrafted features with deep features automatically extracted using the ResNet-LSTM model, aiming to provide a comprehensive and multi-dimensional representation of electrocardiogram (ECG) signals. This approach integrates statistical and physiological insights with representations learned through deep learning, enhancing the system's ability to analyze heart rate dynamics and detect Atrial Fibrillation (AF). The extracted features are categorized into three main types: time-domain features, frequency-domain features, and spatiotemporal features.

IV.4.1 Time-Domain Features

Several temporal indicators were extracted to capture heart rate dynamics, including:

1. HR_Mean

- **In AF:** The heart rate is relatively high due to a large number of beats occurring within a short period, often exceeding 100 beats per minute (bpm).
- **In Normal Rhythm:** The heartbeats are consistent and moderate, typically within the normal range of 60–100 bpm.
- **Importance for Classification:** The mean heart rate (HR_Mean) serves as an essential indicator of abnormal heart rhythms. Elevated heart rates above 100 bpm are indicative of arrhythmic conditions like atrial fibrillation (AF), making HR_Mean a key feature in distinguishing AF from normal rhythm.

2. HRV_SDNN

- **In AF:** There is significant variation in the spacing between QRS complexes, leading to a high HRV_SDNN.

- **In Normal Rhythm:** The QRS intervals are nearly equal, resulting in a low HRV_SDNN.
- **Importance for Classification:** HRV_SDNN reflects the autonomic nervous system's regulation of the heart. In AF, the irregularity in heartbeat intervals leads to high variability, which is a distinctive feature that helps in detecting AF compared to a normal sinus rhythm with low HRV.

3. RR_Interval_Mean

- **In AF:** The time intervals between heartbeats are shorter due to the rapid rhythm.
- **In Normal Rhythm:** RR intervals are regular and fall within normal physiological ranges.
- **Importance for Classification:** The mean RR interval provides insight into the regularity of the heart rhythm. Shorter, irregular RR intervals are a hallmark of AF, which makes this feature valuable for distinguishing AF from normal rhythms.

4. RR_Interval_Std

- **In AF:** The large variability between intervals results in a high standard deviation.
- **In Normal Rhythm:** The intervals are regular, leading to a low standard deviation.
- **Importance for Classification:** The standard deviation of RR intervals (RR_Interval_Std) quantifies the irregularity of the heart rhythm. A high standard deviation is indicative of AF, making this feature essential for detecting the disorder, as AF is characterized by highly variable RR intervals.

5. QRS_Duration

- **In AF:** Despite rhythm irregularities, QRS duration remains within the normal range (80–100 ms).
- **In Normal Rhythm:** The QRS complex is narrow and uniform.
- **Importance for Classification:** The duration of the QRS complex is an important indicator of ventricular depolarization. In AF, the QRS duration remains mostly unaffected despite irregular rhythms, so it can be used to differentiate AF from other arrhythmias that may affect the duration.

IV.4.2 Frequency-Domain Features

Frequency features were computed using spectral power analysis, which reflects autonomic nervous system activity:

1. LF_Power

- **In AF:** Autonomic regulation is disrupted, leading to a reduction in LF_Power.
- **In Normal Rhythm:** LF_Power is within the normal range.
- **Importance for Classification:** LF_Power is associated with the sympathetic nervous system's regulation of the heart. A decrease in LF_Power in AF suggests disrupted autonomic control, making this feature significant for detecting AF, where autonomic regulation is typically impaired.

2. HF_Power

- **In AF:** HF power is unstable or slightly elevated due to rapid fluctuations in the signal.
- **In Normal Rhythm:** HF_Power falls within the expected range.
- **Importance for Classification:** HF_Power reflects parasympathetic nervous system activity and respiratory influences. In AF, HF_Power can become unstable, highlighting the irregular autonomic control seen in AF, which is valuable for classification purposes.

3. LF/HF_Ratio

- **In AF:** Due to reduced LF and unstable HF, the ratio is generally low or fluctuating.
- **In Normal Rhythm:** Both LF and HF powers are balanced, resulting in a ratio close to 1 or slightly higher.
- **Importance for Classification:** The LF/HF ratio is often used to assess the balance between sympathetic and parasympathetic nervous system activity. In AF, the imbalance between LF and HF powers results in a lower ratio, which serves as a distinguishing feature for AF detection.

IV.4.3 Spatially localized and temporally features

A deep neural network architecture based on ResNet-LSTM was developed to extract rich, discriminative representations from raw ECG signals. The model comprises the following components:

- **Input Layer:**The ECG signal is provided to the model as a time-series input with the shape (number of samples × number of channels).
- **Initial Convolutional Layer (Conv1D):**A 1D convolutional layer with 64 filters and a kernel size of 7 is applied to extract initial spatial patterns. This is followed by Batch Normalization and ReLU activation to promote stable and efficient learning.
- **Residual Blocks:** Four residual blocks are included in the architecture. Each block consists of Conv1D layers, Batch Normalization, and shortcut connections to enable smoother gradient flow and more effective training of deeper layers.
- **LSTM Layers:** The output of the residual blocks is passed through two LSTM layers with 128 units each, which capture long-term temporal dependencies in the ECG signal—essential for identifying irregularities associated with AF.
- **Fully Connected Layers:**The temporal output is then processed by two dense layers with 256 and 128 neurons respectively, both utilizing ReLU activation. The output is a high-dimensional representation capturing spatially localized and temporally encoded features.
- **Feature Extractor Model:** A sub-model was constructed to extract only the aforementioned features (excluding the classification layer), enabling their use in a separate classifier.

IV.5 Model Training and classification based Support Vector Machine (SVM)

After extracting the spatially localized and temporally encoded features, along with the time-domain and frequency-domain features, the final model is trained using a Support Vector Machine (SVM) classifier.

* **Feature Fusion:**The spatially localized and temporally encoded features obtained from the ResNet-LSTM model were concatenated with handcrafted fea-

tures representing key temporal and frequency-domain characteristics. This was achieved using np.concatenate along the feature axis.

* **Data Standardization:** Prior to fusion, the handcrafted features were standardized using Scikit-learn's StandardScaler to align them with the scale of the ResNet-LSTM-derived features.
* **SVM Training:** An SVM classifier with a Radial Basis Function (RBF) kernel was employed due to its effectiveness in capturing non-linear decision boundaries. The regularization parameter C was set to 1.0, and gamma was configured to 'scale' for automatic adjustment based on input variance.

IV.6 Conclusion

In conclusion, this chapter represents an important step toward developing an intelligent approach for diagnosing atrial fibrillation using artificial intelligence techniques. By understanding the adopted methodology, processing the data, recognizing relevant patterns, and extracting the desired features, a comprehensive framework has been established to achieve this goal. In the next chapter, we will present the results obtained after completing all the previously mentioned steps.

CHAPTER V

EXPERIMENTAL RESULTS AND EVALUATION OF THE PROPOSED SYSTEM'S PERFORMANCE

V.1 Introduction

After presenting the adopted methodology in the previous chapter, this chapter provides a detailed presentation of the results obtained following the system deployment. It also outlines the tools and techniques employed in this sens. Moreover, this chapter includes a systematic evaluation of the achieved results in order to assess the effectiveness and accuracy of the proposed approach.

V.2 Development Environment and Tools Used

V.2.1 Python Language

Python is a high-level, general-purpose programming language that was developed at the Dutch Institute for Mathematics and Computer Science (CWI) in Amsterdam by Guido van Rossum in the late 1980s, with its first release in 1991 [71]. Although it had limited adoption initially, the language has experienced significant growth in recent years, ultimately ranking first in the Tiobe Index, thanks to its robust capabilities in machine learning, data science, and artificial intelligence. Python is widely used for web development, data analysis, algorithm design, and task automation. Its versatility allows it to be applied across a broad spectrum of applications without being limited to any specific problem domain. With its ease of learning and use, along with a strong and extensive developer community, Python has become one of the most popular and in-demand programming languages in the global tech market today [72] .

- **Reason for using Python**

Python is considered one of the most prominent programming languages used in the fields of artificial intelligence and machine learning, due to its simplicity, ease of learning, and the availability of a wide range of specialized libraries that enable the efficient execution of complex operations without the need to write code from scratch.

For instance, the Scikit-learn library offers a broad collection of machine learning algorithms, such as linear regression, logistic regression, and support vector machines (SVM). Other libraries like spaCy and NLTK support natural language processing tasks. Additionally, libraries such as TensorFlow, PyTorch, and Keras are widely used for developing deep learning models. On the other hand, libraries like NumPy, Pandas, and Seaborn are essential for data processing, analysis, and visualization.

The integration of these tools within a single environment enhances development efficiency and reduces the time and effort required to implement AI projects, making Python the optimal choice for researchers and developers in this field [73].

- **google colab**

Google Colab (short for Google Colaboratory) is a free interactive development environment based on Jupyter Notebook, developed by Google to support education and research in the fields of artificial intelligence and data science. The platform allows users to write and execute Python code directly from their browser, without the need to set up a local environment. Google Colab offers several important features, including:

  * Free access to GPUs and TPUs, enabling users to accelerate the training of deep learning models.
  * Integration with Google Drive, which facilitates saving, sharing, and collaborative work on projects.
  * A pre-configured environment with popular libraries such as TensorFlow, PyTorch, Scikit-learn, and NumPy, eliminating the need for manual installation.
  * An interactive interface that supports text, equations, images, and graphs, making it suitable for educational and documentation purposes.
  * The ability to import data from various sources, including Kaggle and GitHub.

In general, Google Colab is a powerful and free tool that enables researchers, students, and developers to build machine learning models easily and efficiently, making it a preferred platform in academic and scientific settings [74].

V.2.2 Configuration Hardware

We present in Table V.1 the specifications of the local hardware used

	Machine 1	Machine 2
Manufacturer	Hp	Lenovo
Type	DESKTOP-5FSD5TD	ThinkPad L380
Processor	Intel(R) Core(TM) i5-4300U CPU @ 1.90GHz 2.50GHz	Intel® Core™ i5-8250U 8 Cores
GPU	Intel HD Graphics 4400	Intel UHD Graphics 620 (KBL GT2)
Hard Disk	Non précisé	Unknown
RAM	8 GB	8 GB
Operating System	Windows 10 Pro (64-bit)	Ubuntu 24.04.2 LTS (64-bit)
Other details	Touch support (2 points)	Wayland / Kernel: 6.11.0-24-generic

Table V.1: Specifications of the local hardware used.

- **Online**

We used **the T4 GPU** provided by **the Google Colab** environment for training and evaluating the model.

V.3 Performance measures used

After developing a machine learning model, the next step involves evaluating its performance to ensure its effectiveness. This is achieved by employing a variety of performance metrics on a test dataset that is separate from the training data. The selection of appropriate evaluation metrics is critical, as it directly impacts the accuracy of the obtained results and the decisions based on the model's outcomes.

V.3.1 Confusion Matrix

The confusion matrix is a fundamental analytical tool in supervised machine learning, allowing for a precise evaluation of classification model performance by comparing predicted outcomes with actual values. It presents the results in a structured format that highlights correctly classified instances, such as true positives and true negatives, while also illustrating classification errors like false positives and false negatives[13]. Figure V.1 provides an illustrative example of a confusion matrix for a binary classification model:

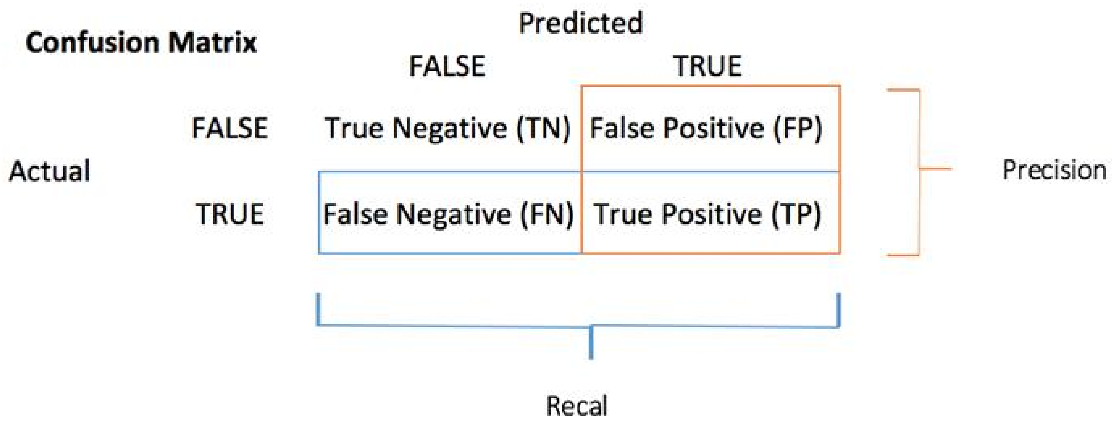


Figure V.1: Confusion Matrix[13]

The confusion matrix comprises four fundamental components used to evaluate the performance of classification systems[13]:

* **True Positives (TP):** Instances correctly predicted as positive.
* **False Positives (FP):** Instances incorrectly predicted as positive.
* **True Negatives (TN):** Instances correctly predicted as negative.
* **False Negatives (FN):** Instances incorrectly predicted as negative.

This matrix provides a detailed analysis of model performance, helping to identify the most common types of errors and guiding parameter adjustments to enhance accuracy. It is widely employed in statistics, data mining, machine learning models, and various artificial intelligence applications [13].

V.3.2 Classification Accuracy

Accuracy is a commonly used metric for evaluating the performance of classification models. It represents the ratio of correctly classified samples to the total number of samples in the dataset[48]. Mathematically, accuracy is calculated as the sum of true positives (TP) and true negatives (TN) divided by the total number of samples.

Accuracy serves as a good indicator when dealing with balanced datasets, where different classes are approximately equally represented. However, it can be misleading in cases of class imbalance, as a model may show high accuracy while neglecting the minority class. Therefore, in such scenarios, it is recommended to use additional metrics such as Precision, Recall, and the F1-Score to more comprehensively and fairly evaluate the model's performance across different classes [75].The following is the mathematical expression for accuracy

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision and Recall**

Precision and Recall are among the most important metrics used to evaluate the performance of classification models, especially in cases where the classes are imbalanced. Precision refers to how accurate the model's positive predictions are. It is calculated as the ratio of correctly predicted positive samples to the total number of samples predicted as positive. Recall, on the other hand, reflects the model's ability to retrieve all actual positive samples. It is computed as the ratio of correctly predicted positive samples to the total number of actual positive samples in the dataset. Both metrics are used together to provide a more comprehensive evaluation of the model's performance, particularly in applications where the balance between correct and incorrect predictions is critically important [48][76].The following is the mathematical expression for Precision and Recall

$$\text{Precision} = \frac{TP}{TP + FP} \tag{V.1}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{V.2}$$

- **F1-Score**

The F1-Score is one of the fundamental metrics for evaluating the performance of classification models, especially in cases where the data is imbalanced. It represents the balance between precision and recall and is calculated as their harmonic mean. This metric is used to provide a comprehensive view of the model's performance by combining its ability to reduce false positives and increase true positives [48].

Mathematically, it is expressed by the following formula:

$$F1\text{-}Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

The F1-Score is particularly useful in applications that require a careful balance between precision and recall, such as text classification, spam detection, and named entity recognition, where focusing on only one of the two metrics is not sufficient for making accurate decisions [77].

V.3.3 ROC Curve and AUC Score

The Receiver Operating Characteristic (ROC) curve is an important analytical tool for evaluating the performance of binary classification models. The curve is plotted by representing the True Positive Rate (TPR) against the False Positive Rate (FPR) at different threshold levels. The Area Under the Curve (AUC) indicates the model's ability to distinguish between positive and negative classes, where an AUC value of 1.0 indicates perfect discrimination, while a value of 0.5 indicates random performance. AUC values above 0.80 are typically considered clinically useful, whereas values below 0.80 are of limited utility. When interpreting AUC values, it is important to consider the 95% confidence interval, as it reflects the degree of uncertainty around the AUC value. ROC analyses are also used to determine the optimal threshold value for a diagnostic test, which is the value that maximizes both sensitivity and specificity of the test[78].

V.4 Classification Results

During the preparation of the training data for the final model designed to classify atrial fibrillation (AF), a significant imbalance was observed between the number of AF cases and normal cases. Specifically, the dataset contained approximately 738 samples labeled as AF, compared to 5050 normal samples. Previous studies have shown that such imbalance is common in this type of application and can be attributed to several challenges most notably, the difficulty in obtaining a sufficient number of pathological cases due to patient privacy concerns and the reluctance of many physicians and medical institutions to share clinical data for public research purposes.

To address the class imbalance issue and ensure the development of an unbiased and generalizable model, the Synthetic Minority Over-sampling Technique (SMOTE) was applied. SMOTE is considered one of the most effective data augmentation techniques for handling class imbalance. By applying SMOTE, additional synthetic samples of the AF class were generated, increasing the number of AF instances to 5050 equal to that of the normal class resulting in a fully balanced dataset of 10,100 samples.

V.4.1 Evaluation of Classification Performance

After training the final model using the SVM algorithm, the model achieved a training accuracy of 95.61% and a test accuracy of 94.46%, indicating that it effectively learned the patterns in the training data. Moreover, the generalization gap the difference between training and test accuracy was only 1.15%, which is remarkably small. This suggests that the model is capable of generalizing well to unseen data and does not suffer from overfitting. In other words, the model did not merely memorize the training data but learned in a way that enables it to perform well on new, external data.

```
=== Model Performance Summary ===
Training Accuracy: 0.9561
Test Accuracy: 0.9446
Difference: 0.0115
```

Figure V.2: Model Performance Summary

V.4.2 Classification Report

The classification report depicted in the figure V.3 summarizes key performance metrics including precision, recall, and F1-score for each class. It shows that the model achieved balanced and high performance on both normal (N) and atrial fibrillation (AF) classes, with an overall accuracy of 94%.

	precision	recall	f1-score	support
0	0.93	0.96	0.94	1001
1	0.96	0.93	0.94	1019
accuracy			0.94	2020
macro avg	0.94	0.94	0.94	2020
weighted avg	0.94	0.94	0.94	2020

Figure V.3: Classification Report

V.4.3 Confusion Matrix

From the obtained Confusion matrix presented in the figure V.4, we can attest that the number of correctly classified cases is 958 for normal arrhythmia and 947 for atrial fibrillation, indicating high accuracy in distinguishing between normal and atrial fibrillation cases.

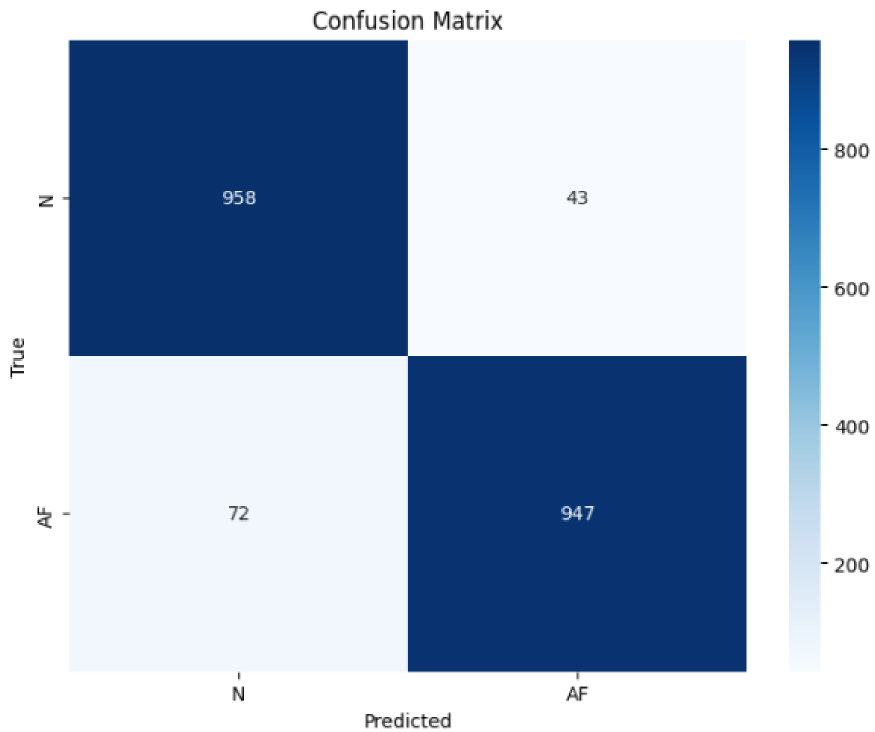


Figure V.4: Confusion Matrix

V.4.4 ROC Curve (Receiver Operating Characteristic)

The ROC curve exposed in the figure V.5indicates the model's high ability to distinguish between the two classes, as the AUC reached 0.96, reflecting excellent performance.

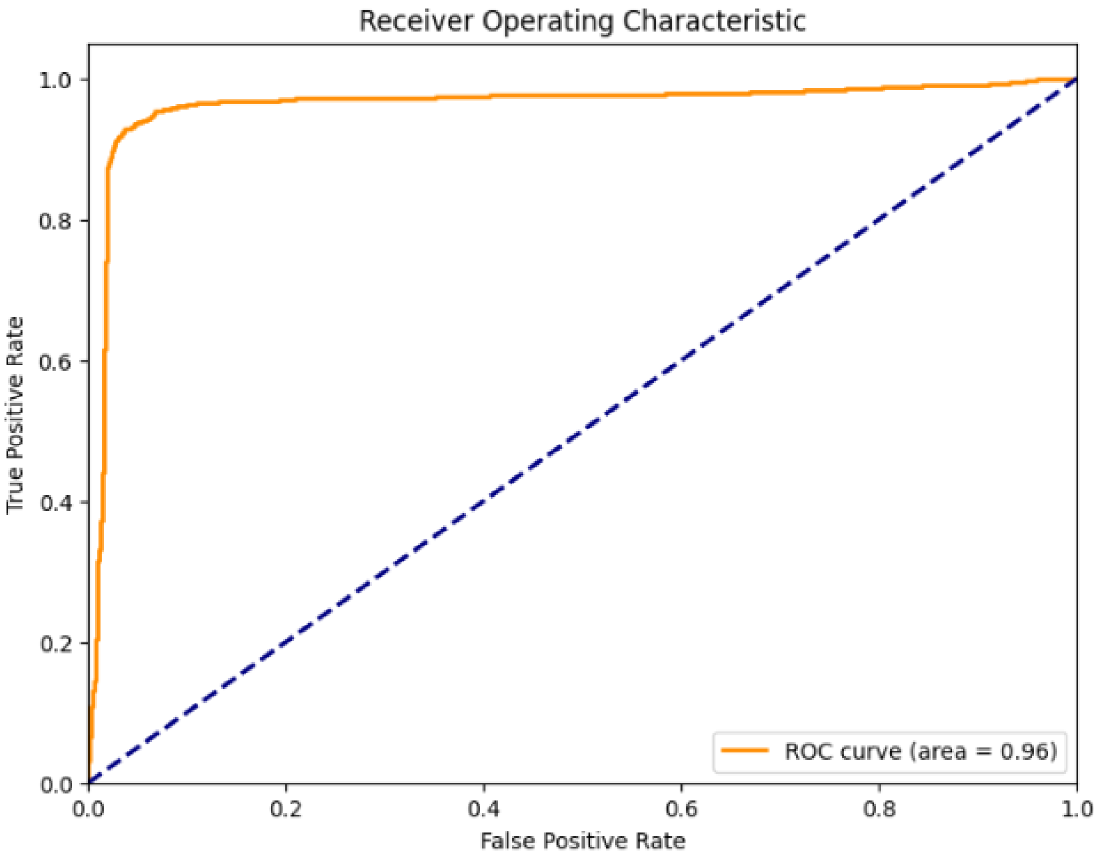


Figure V.5: Receiver Operating Characteristic

V.4.5 Precision-Recall Curve

figure V.6 shows the relationship between precision and recall at different thresholds. We notice that the model maintains high precision across most values, which means it does not make many mistakes when predicting the positive class, while also achieving good recall, indicating its ability to correctly retrieve most of the actual positive samples.

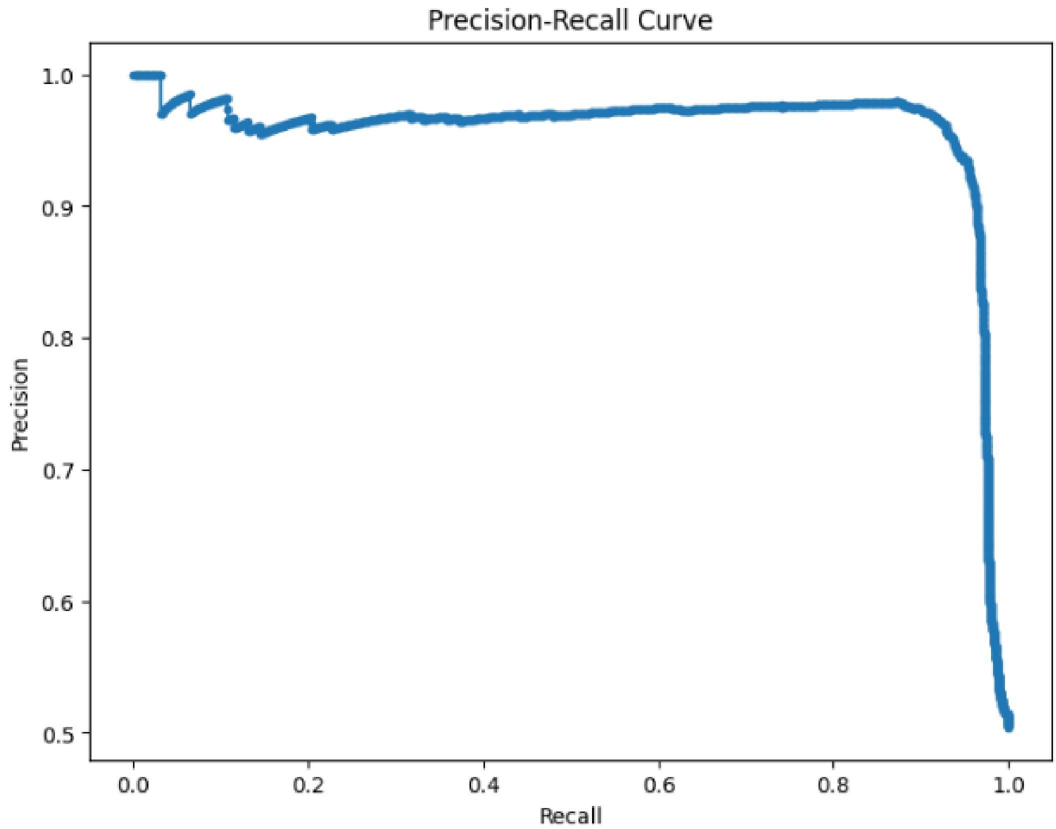


Figure V.6: Precision-Recall Curve

V.5 Comparison of the Performance of Our approach against state-of-the-art approaches

In the context of evaluating the performance of different models for Atrial Fibrillation (AF) classification, a comprehensive comparison was made between the proposed model and other models based on deep learning techniques such as ConvMixer + Transformer, MVPNNet, and CNN + RNN. Well-known datasets such as PhysioNet / CinC 2017 and MIT-BIH were used. The results showed that the proposed model, which relies on Support Vector Machines (SVM), achieved the best performance in terms of accuracy, outperforming the other models.

The following table V.2 outlines the details of the different models and the performance achieved with each:

Type of Condition	Model Used	Dataset	Results	Reference
Normal and Atrial Fibrillation	ConvMixer + Transformer	PhysioNet / CinC 2017	Accuracy = 91.66%	[55]
Atrial Fibrillation Prediction	MVPNNet	Not specified	Accuracy = 89%	[56]
Normal and Atrial Fibrillation	CNN + RNN (end-to-end)	MIT-BIH (MITDB)	Accuracy = 89.3%	[59]
Normal and Atrial Fibrillation	SVM (Final Model)	PhysioNet	**Accuracy = 94%**	**Proposed Method**

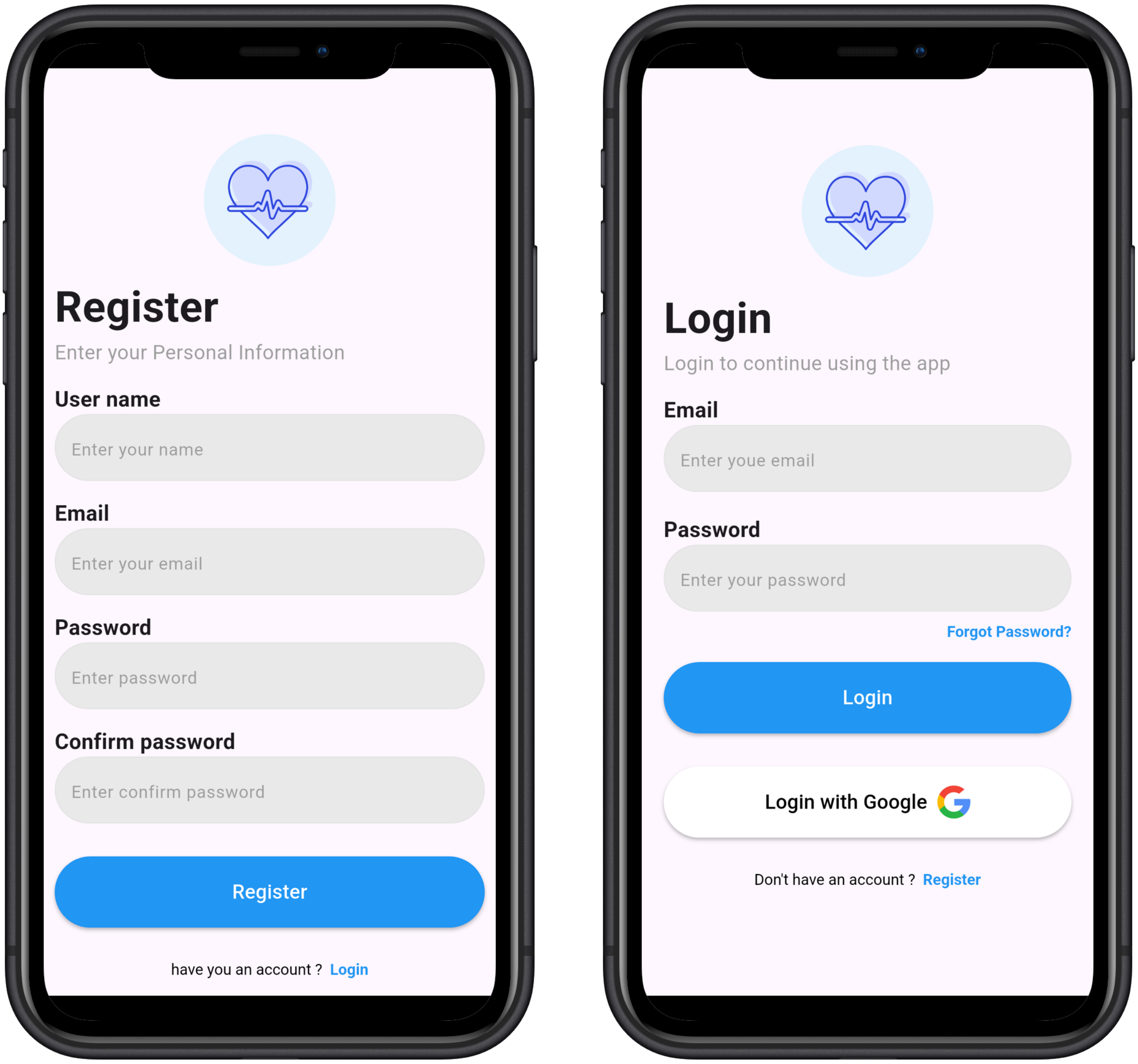
Table V.2: Comparison of the Performance of Our Approach against state-of-the-art approaches

Based on this comparison, it can be concluded that the proposed model delivers superior performance in terms of accuracy compared to the other models, indicating its effectiveness in Atrial Fibrillation detection, providing a powerful tool for diagnosis.

V.6 User Interface Design in Mobile application environment

The developed mobile application allows cardiologists to register and create a personal account that grants them access to a dedicated dashboard. Through this interface, the physician can register their patients, enter their health information, and upload their electrocardiogram (ECG) recordings. Additionally, the system offers continuous remote monitoring of the patients' condition, as the intelligent model analyzes the vital signals and alerts the physician in case any abnormal activity is detected (such as atrial fibrillation). This enables immediate medical intervention, thereby enhancing the chances of early response and prevention, especially in critical situations, without requiring the patient's presence in a clinic or hospital.

Figure depicts V.7 the graphical user interfaces (GUIs) of the mobile application that was developed as part of this project :



A **B**

Figure V.7: Doctor registration (A)and login interfaces(B) in the mobile application

Once the doctor completes the registration and successfully logs into the system, he is directed to the Patient List Interface. This interface displays the personal and medical information of all registered patients, including name, age, blood type, and gender. It allows doctors to efficiently monitor the patient's profile and select individuals for further action such as ECG monitoring or medical intervention.

To add a new patient, the doctor can tap on the "+" button located at the bottom right corner of the interface. This action triggers the appearance of the "Add New Patient" Interface, which contains a structured form with fields for entering the patient's name, age, gender, and blood type. Once the required information is filled in, the doctor can save the entry by clicking the "Save" button, or cancel the operation by selecting Cancel .The following (figure V.8) designs a display of the graphical user interfaces illustrating the interactive sequence of the system as experienced by the user (the doctor):

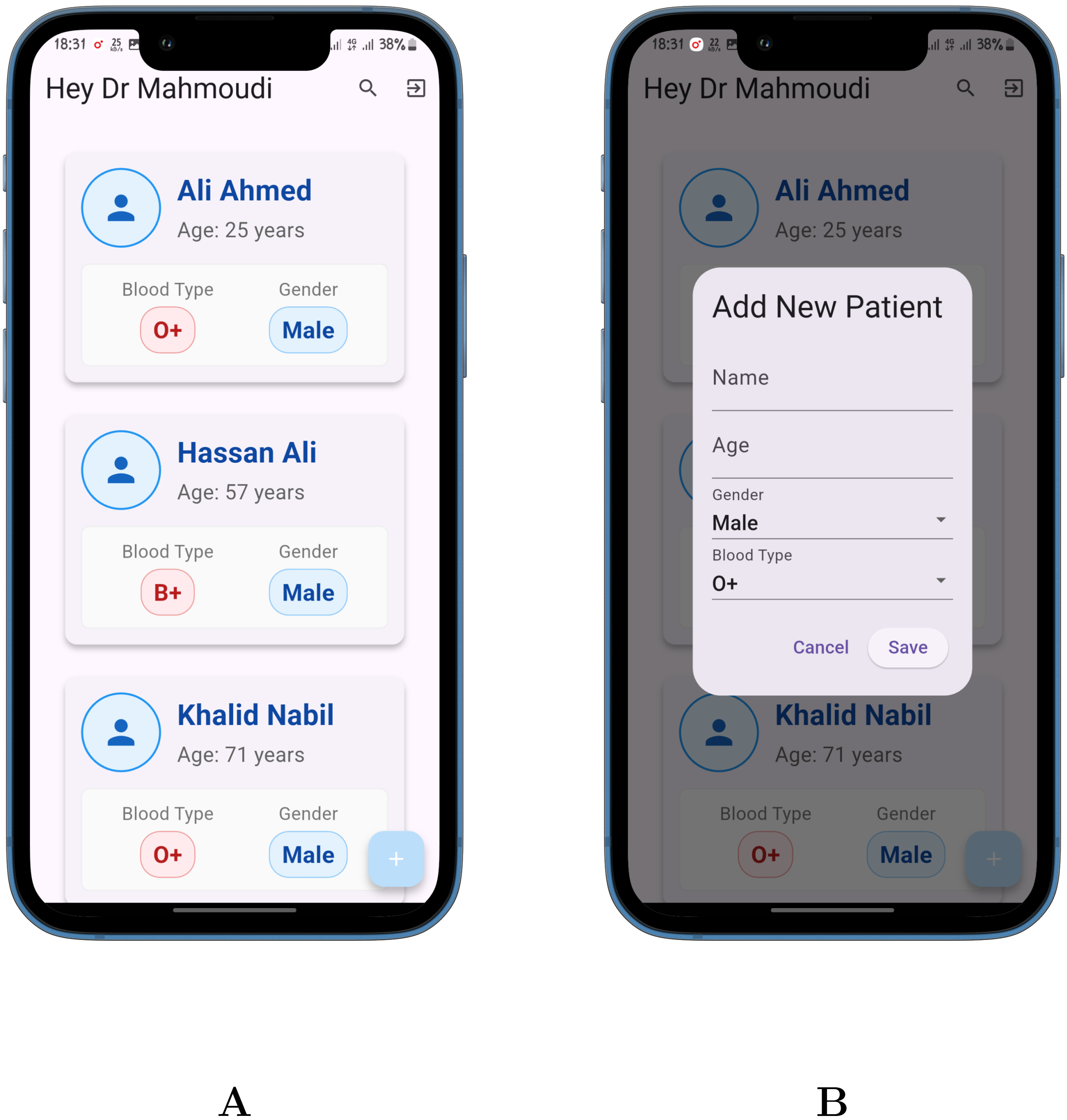


Figure V.8: Patient list for the Doctor in (A) and adding new patient interfaces in (B), within the mobile application

After the physician registers their patients in the application, they can continuously monitor their health status remotely. During the follow-up period, if a case of atrial fibrillation is detected for patients, the physician immediately receives a real-time notification through the mobile application. This enables the doctor to take the necessary medical actions promptly and efficiently, thereby enhancing the chances of early intervention and improving the quality of the provided healthcare.

The displayed interface exposed in the figure V.9 represents the notification received by the physician through the mobile application when a risk related to Atrial Fibrillation (AF) is detected in a patient. The interface presents the patient's details, including name, age, and current cardiac condition. The indicator "Arrhythmia Detected: Normal" signifies that the patient's heart rhythm is currently stable with no abnormalities. Additional information is also provided, such as the date and time of the ECG recording and the date of the last recorded AF episode.

This interface serves as an effective tool for remote patient monitoring, allowing physicians to be immediately informed of any critical developments that may require medical intervention. It enhances the speed of clinical decision-making and contributes to timely and efficient healthcare delivery in emergency situations.

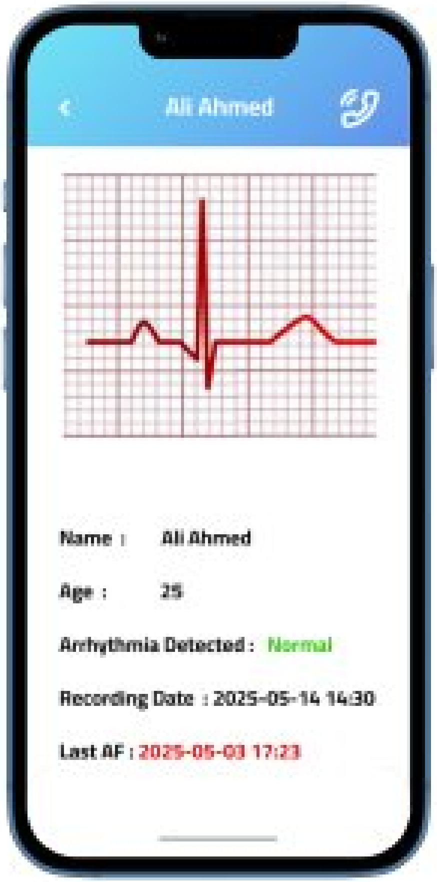


Figure V.9: Mobile application interface displaying a patient's ECG status and notifying the physician of the last recorded Atrial Fibrillation (AF) episode. The current heart rhythm is classified as normal.

V.7 Conclusion

In this chapter, we presented the programming language and tools that were most effective in training our model. Finally, we discussed the classification results obtained and affirmed that the proposed model demonstrated superior performance and higher accuracy compared to the other models.

GENERAL CONCLUSION

Atrial Fibrillation (AF) is one of the most common forms of cardiac arrhythmia, characterized by irregular heartbeats that can lead to impaired blood flow and increase the risk of cerebrovascular events such as strokes or heart attack. Early detection of AF is critical in preventing the serious complications that may result from it. Indeed, people with AF often have risk factors such as: hypertension, coronary artery disease that also increase the likelihood of heart attacks where AF may occur during or after a heart attack as a complication.

In light of the positive outcomes achieved by this project, an intelligent system based on artificial intelligence was developed to facilitate early heart attack detection through monitoring atrial fibrillation as a key indicator. Deep learning and machine learning techniques were employed to analyze ECG signals directly, enabling real-time alerts to physicians upon detecting any abnormalities, allowing for prompt intervention before a heart attack occurs. The system was implemented using an ECG sensor and the ESP8266 module for wireless communication, transmitting data to a server where it was processed and analyzed in real-time. The results demonstrated that the proposed model achieved an accuracy rate exceeding 94% in classifying cardiac signals, confirming its effectiveness in early atrial fibrillation detection, particularly when compared to traditional methods in terms of speed, accuracy, and timely medical response.

Additionally, this study demonstrates that the integration of artificial intelligence and Internet of Things (IoT) technologies represents a significant advancement in medical diagnostics. It reduces human error and accelerates clinical decision-making, enhancing the overall efficiency of medical responses. The proposed system plays a pivotal role in improving healthcare quality, ensuring timely medical interventions, and reducing the mortality rates associated with diagnostic delays in heart-related events.

Based on these encouraging results, future work can expand to include the diagnosis of a broader range of cardiac conditions beyond atrial fibrillation. The aim is to develop a comprehensive and intelligent system capable of detecting various heart disorders with high accuracy and efficiency.

The generalization of this system could mark a significant breakthrough in medical diagnostics and pave the way for the adoption of real-time automated diagnostic tools as part of a clinical decision support system. Therefore, it is recommended to integrate such intelligent systems into the daily practices of cardiologists, given their crucial role in improving healthcare quality and enabling timely interventions.

With these advancements, the future holds significant potential for expanding the use of these intelligent systems, which could further enhance the effectiveness of modern medicine and reduce the burden on global healthcare systems.

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