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THESIS REPORT

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by

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Deep Learning Approaches for Stroke Detection Using CNN and Transfer Learning Techniques

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Abstract

This project explores the application of artificial intelligence (AI) techniques to enhance the diagnosis of stroke disease through medical image classification. Leveraging the power of neural networks, we conducted a comparative study involving popular transfer learning techniques such as VGG16, VGG19, and ResNet-50. While these complex architectures demonstrated their potential, we also recognized the pitfalls of deep models, leading us to introduce a simpler Convolutional Neural Network (CNN) model. Through rigorous evaluation, our proposed CNN model achieved an exceptional accuracy of 99.60%, underscoring the efficacy of a streamlined approach. Our findings emphasize the balance between sophisticated methodologies and pragmatic solutions, showcasing how AI can significantly impact medical diagnoses. As a practical application, we developed an intuitive application that enables users to classify medical images, bridging the gap between AI advancements and real-world medical practices. This project contributes to the advancement of AI in healthcare, showcasing the potential for accurate and efficient stroke disease diagnosis.

Keywords: Convolutional Neural Network, Stroke Diagnosis , Medical Image Classification, Artificial Intelligence

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General Introduction

The rapid advancements in artificial intelligence (AI) [1] have ushered in a new era of innovation across various industries, notably in healthcare. One prominent area of application is the diagnosis and treatment of complex medical conditions. Among these conditions, stroke disease stands out due to its critical nature and the pressing need for accurate and swift diagnoses. Traditional methods of diagnosis often rely on the expertise of medical professionals, which can be time-consuming and occasionally prone to human error.

AI, particularly in the form of machine learning and deep learning techniques [2], offers a promising solution to address these challenges. By harnessing the power of neural networks, AI models can analyze intricate patterns within medical images, aiding in the accurate identification of conditions like stroke disease. Transfer learning, a technique that leverages pre-trained neural network architectures, has emerged as a pivotal approach to enhance the performance of these models. Architectures such as VGG16, VGG19, and ResNet-50 have gained prominence for their effectiveness in feature extraction from diverse datasets.

In this context, our project embarks on a comparative exploration of these transfer learning techniques. We delve into their strengths and limitations in the realm of stroke disease diagnosis. Additionally, we recognize the potential complications introduced by deeper architectures and introduce a simpler Convolutional Neural Network (CNN) model as an alternative solution.

Furthermore, we go beyond model development by implementing a practical application that translates AI advancements into real-world utility. This application empowers healthcare professionals with a user-friendly tool for efficient image classification, narrowing the gap between AI research and its tangible impact on medical practices.

here's a brief overview of the context of each chapter :

- chapter 1 Providing foundational of artificial intelligence.
- chapter 2 Exploring the specifics of stroke disease and reviewing existing research related to AI applications in stroke diagnosis.
- chapter 3 Detailing the approach, dataset, model architectures, and the introduction of a simpler CNN model.

- chapter 4 Results, Environment, and Application - Presenting outcomes, analysis, discussing the experimental environment, and showcasing the practical application of AI in medical diagnosis through a user-friendly tool.
- Conclusion and Future Directions - Summarizing findings, discussing implications, and outlining potential avenues for future research and development.

Chapter 1

Background on Artificial Intelligence

Plan

1.1 Introduction

Artificial Intelligence (AI) is a revolutionary field of study that has captured the imagination of researchers, engineers, and enthusiasts alike. It is a concept that has been explored for decades but has gained significant momentum and practical applications in recent years.

At its essence, AI refers to the development of intelligent machines that can mimic human-like cognitive processes, such as learning, reasoning, problem-solving, and decision-making. In this chapter ,we're going to touche upon the concept of Artificial Intelligence and the different areas of its use as well, and Machine learning (ML) which is a field of study in artificial intelligence concerned with the development and study of statistical algorithms that can effectively generalize and thus perform tasks without explicit instructions, and we have come across different types of machine learning.

1.2 Artificial intelligence and types of learning

Data mining refers to the set of techniques that allow the analysis and interpretation of large volumes of data contained in one or more databases to identify trends. It can also be defined as an interdisciplinary field that uses techniques from machine learning, database classification, and visualization to extract information from massive databases. In our study, we focus on classification methods, particularly supervised classification methods.

A traditional computer program performs a task by following precise instructions, consistently in the same way. In contrast, a Machine Learning system does not follow instructions but learns from experience. Consequently, its performance improves as it is "trained" with more data.

Artificial Intelligence (AI) [3], [4] is a collection of algorithms that grant a machine the ability to analyze and make decisions, enabling it to intelligently adapt to situations by predicting outcomes based on acquired data. AI allows computers to perform tasks that humans naturally do, such as recognizing faces, transcribing speech into text, playing chess, sorting messages, detecting suspicious behavior or fraud, etc. The computer's power (memory, speed) enables it to perform these tasks with a performance beyond human capability.The artificial intelligence (AI) and its sub-disciplines is represented in Figure 1.1

Our daily lives involve constant classifications and assessments. When we encounter individuals, we instinctively categorize them based on various factors, influencing our interactions. Similarly,

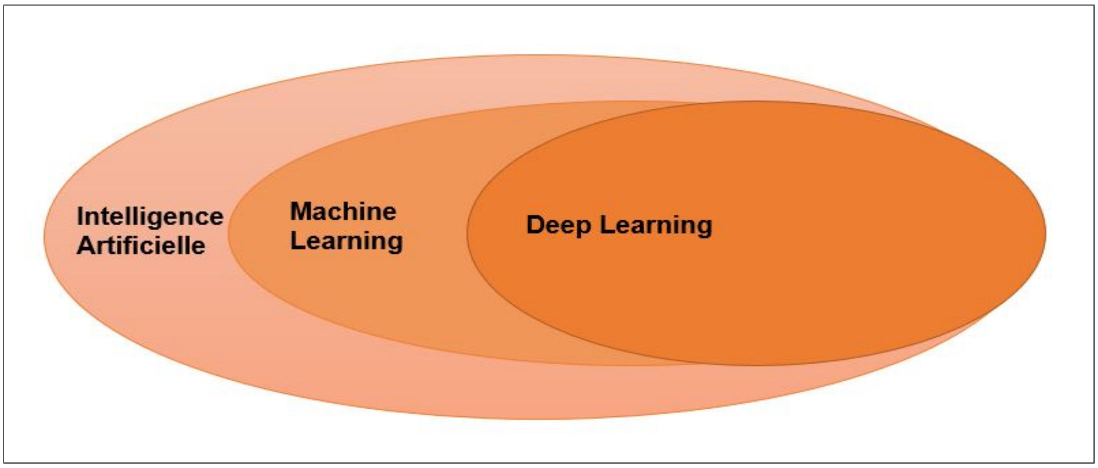


Figure 1.1: Artificial intelligence and its sub-disciplines

when navigating through traffic, we make predictions about other drivers' behavior based on visual cues such as their appearance and vehicle type. In healthcare, we diligently analyze symptoms to reach accurate diagnoses, a cognitive process often mirrored by artificial intelligence (AI). In this context, our focus revolves around addressing the learning challenge, particularly within the medical domain. Here, learning entails a structured and comprehensive approach to vocational training, combining hands-on experience within healthcare facilities with theoretical instruction in medical education centers.

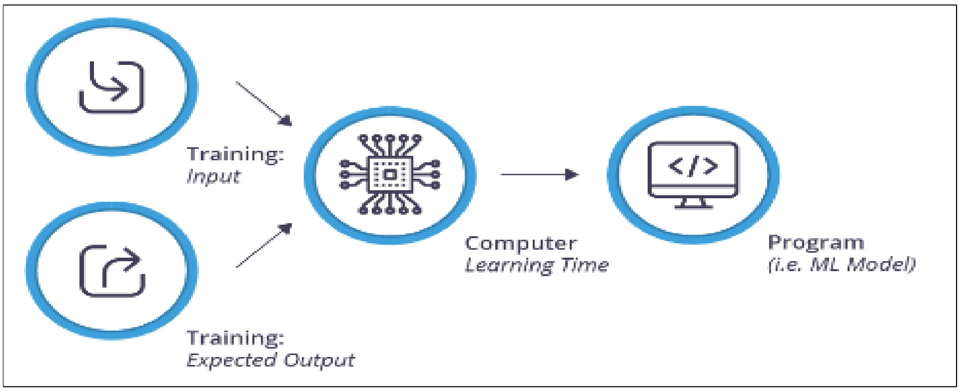


Figure 1.2: Training/Testing Phase in AI: This phase explains how the model will be trained with multiple data to become capable of classifying or predicting new data.

In the context of this work, our main focus lies in the learning problem within the healthcare sector. Learning can be described as a comprehensive and systematic professional development process that combines hands-on experience within a medical facility and theoretical education at a medical training center. .

In Figure 1.2 explains how the model will be trained with multiple data to become capable of classifying or predicting new data.

1.2.1 types of learning

Learning allows young people to acquire early professional experience associated with a diploma, thus giving them every chance of quickly finding employment [5]. Among the types of learning, several are distinguished: a) Natural, b) Artificial.

1.2.1.1 Natural learning

Learning is a lasting modification of behavioral potential resulting from repeated interaction with the environment [6]. Among the modalities of natural learning, we can find:

- Rote learning
- Learning by instruction
- Learning by generalization
- Learning by discovery
- more or less supervised learning
- Autonomous learning

1.2.1.2 Artificial learning

A program has learning capabilities if its behavioral potential on data changes based on its performance as it processes the data. A program possesses learning capabilities if, during the processing of representative examples of data, it can construct and utilize a representation of this processing for its exploitation [7]. There are some related notions of artificial learning:

- Concept Extraction
- Categorization
- Classification
- Knowledge Acquisition
- Prediction

- Generalization
- Understanding
- Regression
- Data Mining
- Pattern Recognition

1.3 Machine Learning

Machine Learning is a concept that is gaining more and more attention in the world of computer science and is related to the field of artificial intelligence. Also known as "apprentissage statistique" (statistical learning), this term refers to a process of development, analysis, and implementation that leads to the establishment of systematic procedures [8], [9].

Historically, this theory gained momentum with the work of mathematicians Vapnik and Chervonenkis in the 1960s. With machine learning, the perspective differs from that of traditional statistics. It no longer focuses on how to find abstract objects such as a probability law, for example, but primarily concentrates on the operational side, which means making decisions from data while making as few errors as possible. The goal is to construct a model directly from the data.

In simple terms, it is a kind of program that enables a computer or a machine to undergo automated learning, in order to perform a variety of highly complex operations. The objective is to make the machine or computer capable of providing solutions to complicated problems by processing an enormous amount of information. This provides an opportunity to analyze and highlight the correlations that exist between two or more given situations and predict their various implications.(see Figure 1.3)

1.4 Different types of machine learning

Machine learning encompasses various types, with supervised learning involving labeled data to predict outcomes like classification and regression. Unsupervised learning, on the other hand, deals with unlabeled data to uncover patterns, including clustering and dimensionality reduction techniques. Semi-supervised learning combines both labeled and unlabeled data to enhance predictive models by leveraging the partial labeling. Additionally, reinforcement learning focuses on training

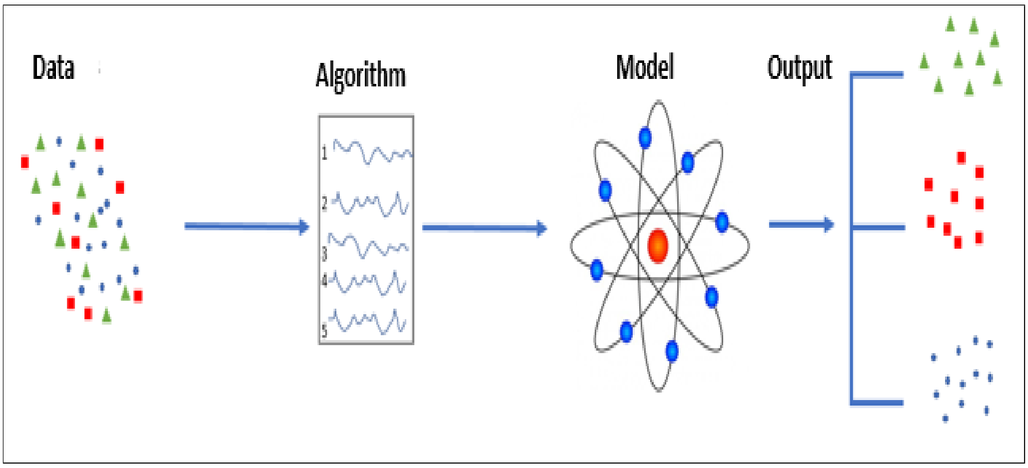


Figure 1.3: The machine learning learning process

agents to take actions in an environment to maximize rewards, often used in robotics and game playing. Lastly, deep learning, a subset of machine learning, employs neural networks with multiple layers to automatically learn intricate representations of data, proving especially effective in image and text analysis.

In Figure 1.4 we will show the different types of learning algorithms

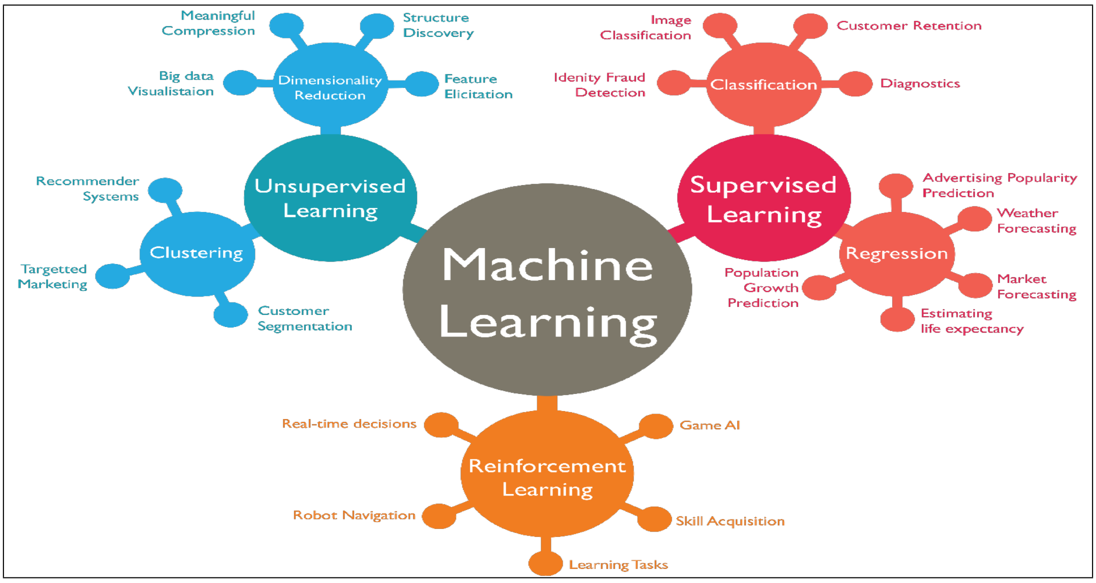


Figure 1.4: Different types of learning algorithms

1.4.1 Supervised Learning

Supervised learning is a method that uses a set of known training classes to adjust a statistical model that can be used for future deployment. This method is in contrast to unsupervised methods, where the classes are unknown (unlabeled). The objective is to determine which group an individual is most likely to belong to. An expert needs to label examples beforehand [10]. The process occurs in

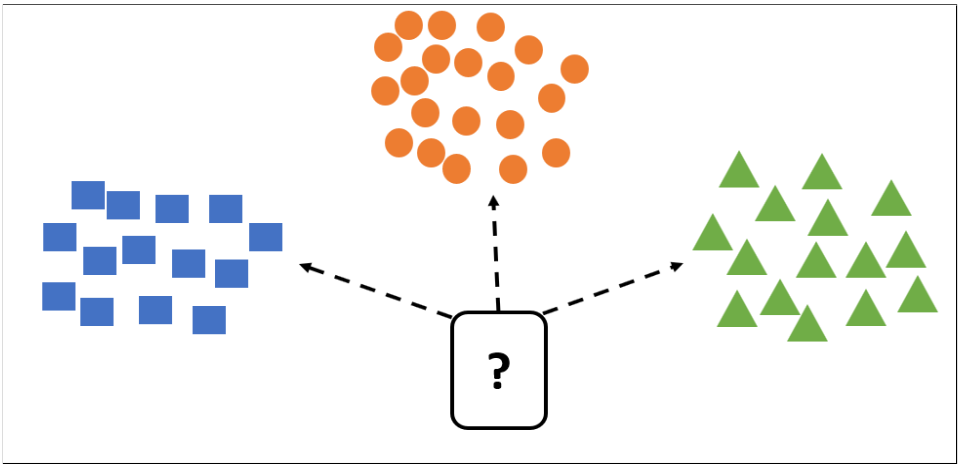


Figure 1.5: Supervised Learning

two phases. In the first phase (offline, known as training), the goal is to determine a model from labeled data. The second phase (online, known as testing) involves predicting the label of a new data point, given the previously learned model.The figure (see Figure 1.5) shows an example of supervised machine learning. Sometimes, it is more appropriate to associate a data point not only with a single class but also with a probability of belonging to each of the predefined classes (this is known as probabilistic supervised learning).

The purpose of a supervised learning algorithm is to generalize what it has "learned" from the processed data by experts to unknown inputs in a "reasonable" manner.

There are several issues with supervised learning, as it requires significant human resources, especially when the number of data points increases. For instance, in well-known examples like medical assistance or diagnosis problems, medical experts are usually the supervisors who annotate the class of objects in the training set based on observed features.

Among the supervised learning methods, the following can be distinguished: - Boosting - Support Vector Machine (SVM) - Mixture of Laws - Neural Networks - k-Nearest Neighbors (k-NN) - Decision Tree - Naive Bayes Classification - Probabilistic Inference - Version Space .

1.4.1.1 Classification

Classification is first used to refer to the partitioning of a set of individuals into classes in such a way that each individual belongs to one and only one class. However, the term "classification" is also used to describe nested systems of classes. In this sense, it can be seen as a statistical operation that involves grouping objects (individuals, variables, or observations) into a limited number of groups (classes or segments) and categorizing individuals based on certain characteristics. There are different types of classification, but one of the most intuitive and widely used is supervised classification. The overall goal of classification is to identify the classes to which objects belong based on descriptive features (attributes, characteristics). Data classification is a challenging problem that arises in various fields, including data mining analysis, and is applied in several sectors, including the medical domain, which is of interest in our study. classification is used to determine groups of patients who are likely to respond similarly to specific therapeutic protocols. Each group gathers patients with similar reactions.

In order to model the change in bond ratings, we used two learning methods that differ in their output nature: regression and classification. Subsequently, we compared both methods using metrics to determine the most suitable one.

These are the main approaches used to address data science challenges when predicting future outcomes of an output variable based on a certain number of observations.

These two scenarios are defined as follows: Classification involves identifying the class membership of new objects based on known previous examples, and the predicted variable can take on discrete values known as classes. We will see that our problem is multi-class, meaning the change in bond rating can be represented by several classes, in contrast to binary classification, which involves an output variable with only two classes. as shown in the following Figure 1.6

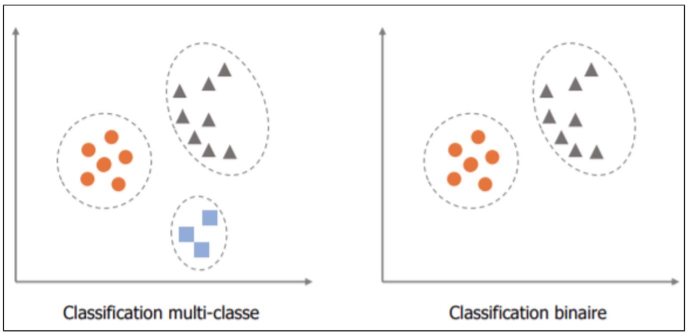


Figure 1.6: Representation of observations: Binary classification and multi-class classification

1.4.1.2 Rregression

Regression is used when predicting a continuous variable, which means it can take any value.
The classes representing the change in bond rating were treated as continuous, and the regression algorithm produced decimal values that we ultimately rounded to obtain a vector of predicted classes. The goal is to predict positive changes in bond ratings (improvement), negative changes (downgrade), or no change. This corresponds to a three-class classification problem -1, 0, 1 or a regression problem with values belonging to the interval [-1, 1].(see Figure 1.7)

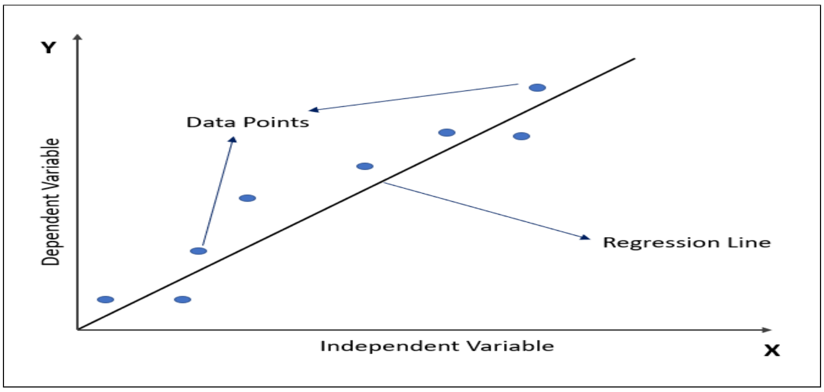


Figure 1.7: Representation of observations about regression model

1.4.2 Unsupervised Learning

Unsupervised learning aims to characterize the data distribution and relationships between variables without discriminating between observed and predicted variables [11]. The task is for the machine to proceed autonomously with data categorization. To achieve this, the system will cross-reference the information provided to it in order to group elements with certain similarities into the same class.(as shown in the following Figure 1.8). Depending on the desired objective, it will be up to the operator or researcher to analyze these groups to draw various hypotheses. The algorithm must autonomously discover the underlying structure based on the data.
There are two categories of unsupervised classification algorithms: hierarchical and non-hierarchical. For example, an epidemiologist studying liver cancer victims might aim to identify explanatory hypotheses. The computer could differentiate several groups and then associate them with various explanatory factors. The objective of unsupervised learning is to group (classify) individuals who are most similar and share similar characteristics . This clustering process can serve different purposes, such as separating individuals belonging to distinct sub-populations, describing data by reducing

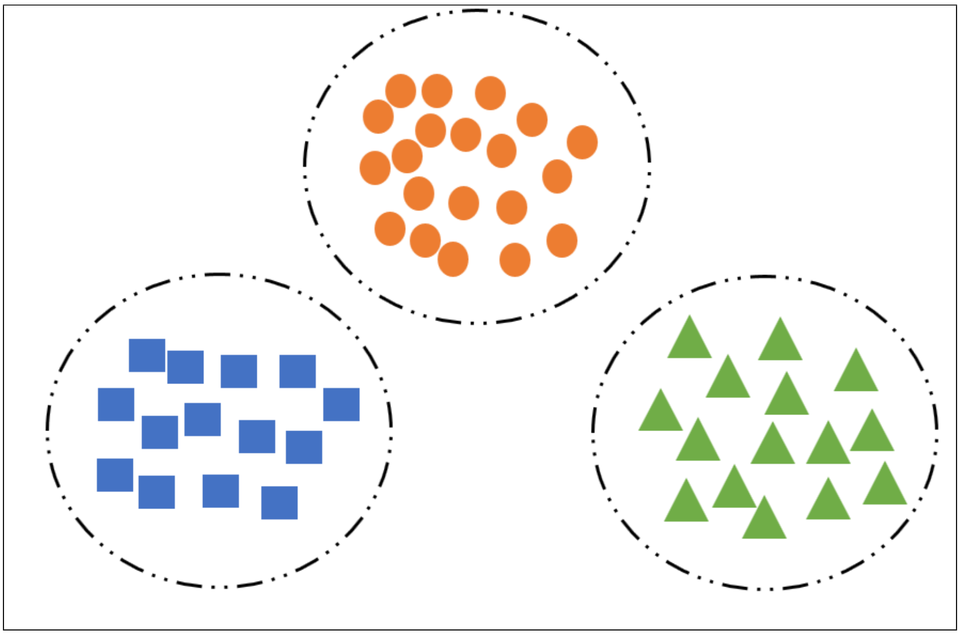


Figure 1.8: Unsupervised Learning

the number of individuals for communication, simplification, or presenting results. Various tasks are associated with unsupervised learning, such as clustering, which involves automatically constructing classes based on available examples.

Clustering techniques aim to decompose a set of individuals into several subsets that are as homogeneous as possible. Association rules are used to analyze relationships between variables or detect associations, and dimensionality reduction.(see Figure 1.9)

Unsupervised learning can also be used in conjunction with Bayesian inference to produce conditional probabilities for each random variable given the others.

Another form of unsupervised learning is data partitioning, which is not always probabilistic.

1.4.3 Semi-Supervised Learning

Semi-supervised learning is a class of machine learning techniques that use both labeled and unlabeled data. It falls between supervised learning, which uses only labeled data, and unsupervised learning, which uses only unlabeled data [12].

It aims to reveal the underlying distribution of "examples" in their feature space. It is employed when data (or "labels") are missing. The model must utilize unlabeled examples that can still provide information (see Figure 1.9). It is often associated with the concept of transductive learning. It is performed on the training data to make predictions on the test data, and only on the test data.

The goal is not to determine the function that minimizes the generalization error but the one that

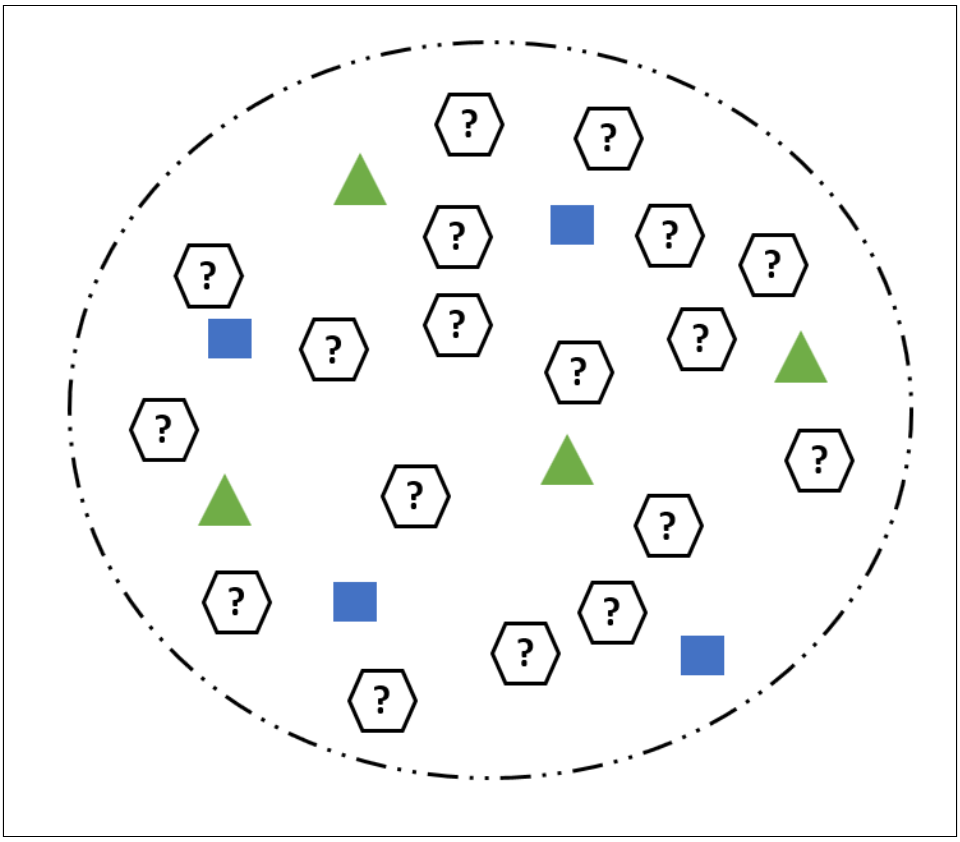


Figure 1.9: Semi-Supervised Learning

minimizes the average error on the test set.

One example of semi-supervised learning is co-learning, where two classifiers learn from a dataset, but each uses a different set of features, ideally independent. For instance, if the data consists of individuals to be classified as men or women, one classifier may use height, while the other uses hairiness.

We can distinguish three approaches in semi-supervised classification..

First, there are general methods that can be applied to any supervised classification method. Then, there are methods specific to predictive models, followed by methods specific to generative models.

There are four algorithms for semi-supervised classification: 1. Co-training. 2. Transductive SVM's 3. Semi-supervised. 4. Graph-based algorithms

Semi-supervised learning aims to tackle problems with relatively few labeled data and a large amount of unlabeled data. This situation can arise when data labeling is expensive, as in the case of web page classification.

1.4.4 Transfer Learning

Transfer learning can be seen as the ability of a system to recognize and apply knowledge and skills learned from previous tasks to new tasks or domains that share similarities [13].(as shown in the following Figure 1.10)

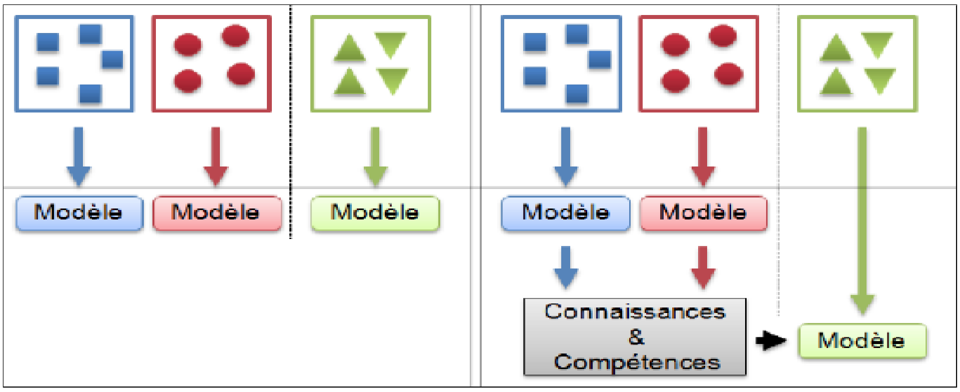


Figure 1.10: Transfer Learning

1.4.5 Reinforcement Learning

Reinforcement learning emerged from the intersection of experimental psychology and computational neuroscience. It relies on a few key concepts based on the fact that an intelligent agent observes the effects of its actions and deduces the quality of those actions from its observations.

Reinforcement learning occurs in our daily lives, whether we are walking, learning a new programming language, or playing a sport.

The algorithm learns a behavior given an observation [14]. The algorithm's action in the environment produces a feedback value that guides the learning process (as detailed in Figure 1.11).

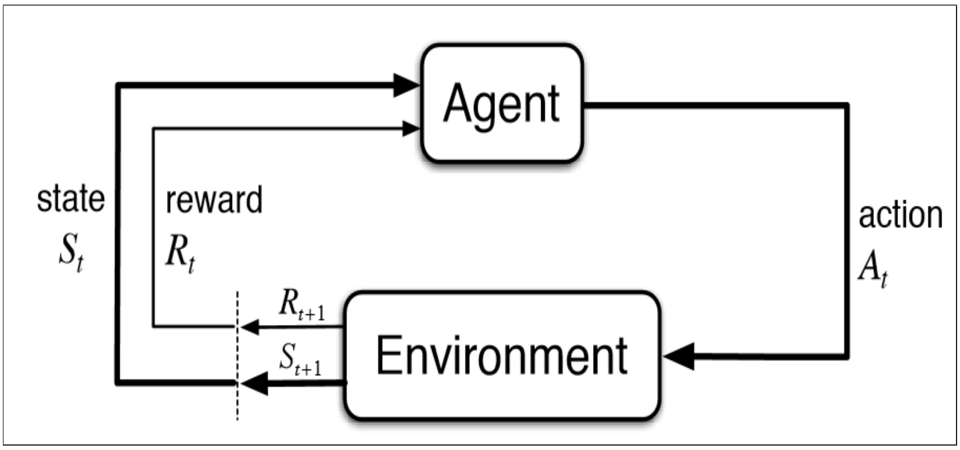


Figure 1.11: Reinforcement Learning

1.5 Parametric and non-parametric algorithms

There are two types of algorithms: parametric algorithms, where the user can modify the algorithm's parameters, and non-parametric algorithms, which do not require any parameter modifications.

1.5.0.1 Non-parametric

Non-parametric approaches (e.g., hierarchical clustering, k-nearest neighbors) are based on the assumption that the closer two individuals are, the more likely they belong to the same class. The distinctive feature of these approaches is that they make no assumptions about the underlying data model. For example, in k-nearest neighbors, we only need to determine the convergence properties as the number of data points increases.

1.5.0.2 Parametric

The second major family of classification methods involves probabilistic approaches, where an assumption is made about the distribution of the data to be classified. This means that we assume knowledge of the model that generated the data. For example, we might consider that individuals in each class follow a normal distribution. The challenge lies in determining or estimating the parameters of these distributions (e.g., mean, variance) and assigning individuals to the most likely class based on the training dataset.

1.5.0.3 Application Areas

As mentioned earlier, Intelligence artificial plays a role in almost every field that involves multidimensional statistics. There is a plethora of domains where AI is used, including finance, security, medicine, the automotive industry, and technology as a whole. To cite some practical use cases of machine learning or statistical learning .

We can mention self-driving cars, with Google's model being the most representative. Recognition tasks (voice, facial, object, or character recognition) in security or information systems (see Figure 1.12).

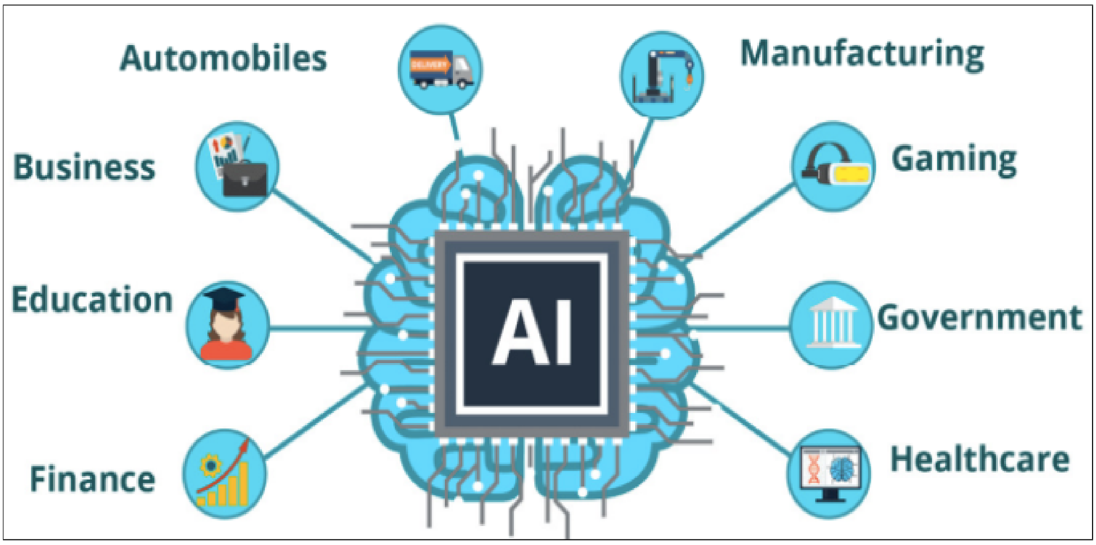


Figure 1.12: Some application domains of artificial intelligence include:

1.6 Conclusion

the diverse landscape of machine learning types, from supervised and unsupervised learning to reinforcement and transfert learning, highlights the remarkable versatility of artificial intelligence (AI). These methodologies have collectively transformed industries by enabling systems to learn, adapt, and make informed decisions from data. Moreover, AI's potential is most pronounced in the realm of medicine. In particular, its proficiency in various machine learning paradigms has revolutionized medical diagnoses. Through AI's prowess in data analysis, it has significantly elevated the accuracy and speed of detecting conditions like multiple sclerosis and strokes. This development not only improves patient outcomes through early identification but also equips healthcare professionals with powerful tools for decision-making.

Chapter 2

State of the art

Plan

2.1 Introduction

Stroke refers to the abrupt disruption of cerebral blood flow, causing a lack of oxygen and nutrients to brain cells and resulting in tissue damage and neurological impairments. It can arise from artery blockage (ischemic stroke) or blood vessel rupture (hemorrhagic stroke), ranking as a major global cause of mortality and disability, necessitating swift intervention for optimal results. Computed Tomography (CT), a vital medical imaging method, is integral for stroke diagnosis and control. Utilizing X-rays and advanced computation, CT scans yield intricate brain cross-sectional images. This technique is pivotal in identifying stroke types, pinpointing locations, gauging brain injury extent, and guiding treatment choices. By harnessing algorithms, notably deep learning, researchers enhance stroke diagnosis via automated CT pattern recognition, ensuring swift and precise outcomes. They also craft algorithms for bra in structure separation from CT scans, aiding injury assessment and intervention planning. CT imaging differentiates treatment approaches for ischemic and hemorrhagic strokes, bolstered by predictive models blending CT images and clinical data for outcome insights, shaping tailored treatment and recovery strategies. With AI-driven automation streamlining CT analysis and telemedicine bridging remote scan access gaps, ongoing research and technological progress amplify CT's stroke management role, vouchsafing refined accuracy, efficiency, and accessibility for optimal patient outcomes.

2.2 Theoretical Background

2.2.1 Stroke in the Medical Field

Stroke is the second deadliest disease in the world and it has always been one of the majorcauses that damage the life and health of human beings [1]. Generally, there are two main typesof stroke: (i) hemorrhagic, which occurs when a cerebral blood vessel suffers a rupture and the blood affects near the affected area, and (ii) ischemic, which happens when a cerebral bloodvessel is blocked and prevents blood from flowing and reaching other parts of the brain [11].

The most prevalent cases of stroke are ischemic and the main concern is that they can causethe local death of the tissue where they are located if they prevail for a longer period of time, asthey can cause irreversible harm to the patients' motor functions. There are two main regionsthat characterize a stroke: the infarct core and the penumbra. The former refers to tissue thatis irreversible affected and no longer alive, while the latter refers to tissue that is likely to be recovered only if blood is rapidly supplied to it [13]. The effectiveness of a quick reaction ofneurologists and radiologists is a matter of importance in identifying the penumbra, assessing the damage and determining the most adequate therapy required by patients to salvage as much of the compromised brain tissue as possible.

2.2.2 Medical Images for stroke analysis

To begin with the scrutiny and understanding of the penumbra, specialists rely on biomedical images: X-Ray, MRI and CT. These are examples of popular types of medical images that provide a better internal tissue visualization. Generally, X-Ray imaging is used for fissures and bone displacement, CT for tumors, cancer and stroke detection, and MRI for stroke analysis. Although the type of image completely depends on the medical equipment at hospitals, CT has remained to be one favorite choice for analyzing cerebral flow, as it generates images ofthe bones, soft tissues and blood vessels in the body. However, it still presents limitations that MRI leverages in regards to ischemic stroke detection, as it generates a image with sufficient resolution to have a better visualization of the brain [15].

In principle, the functionality of MRI is based on radio frequency and strong magnetic fields. An MRI scanner is responsible for generating a strong magnetic field, and then it passes a radio signal with different intensity to produce gray scale images of any part of the body. One of the benefits of using MRI is that its wave frequency is harmless to humans, in contrast to how x-ray and CT work. Another advantage of MRI is that it is susceptible to water, which means that it can detect diseases, as in most cases they are detectable due to their varied levels of water in patients and the effect in the brain is that it makes visible the difference between gray and white matter. MRI images can be divided into three main planes: axial, sagittal, and coronal. Figure 2.1 shows an example of each plane of an MRI.

Different types of MRI sequences can be obtained depending on the time period in which the radio frequency pulses (Time Repetition) are applied to the tissue and the time span in which the signal is received (Time Echo). The most common ones are T1-weighted and T2-weighted images. The former is obtained when the time for both TR and TE is short (500 msec and 14 msec), whereas the latter shows a result when there is a longer time in both indicators (4,000 msec and 90 msec). An extra sequence called Flair is generated when both TR and TE are much longer (9,000 msec and

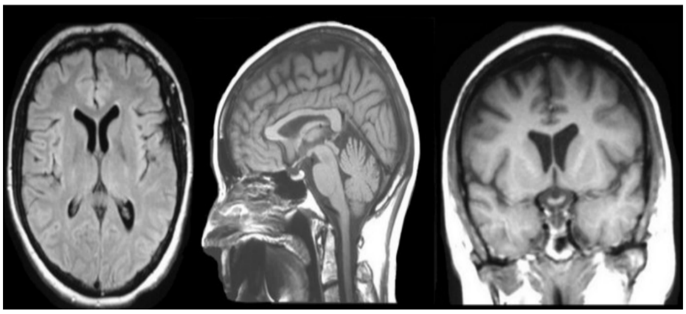


Figure 2.1: Axial, sagittal and coronal planes of an MRI

114 msec). Figure 2.2 shows an example of such sequences.

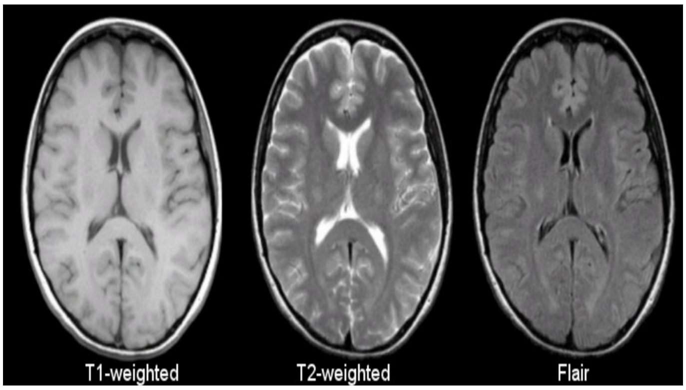


Figure 2.2: Sequences of MRI

Although these types of neuroimages (X-Ray, CT and MRI) are used to facilitate the detection of ischemic stroke, they cannot provide an identifiable penumbra region in cerebral tissue. The final interpretation of results, the determination of the diagnosis, and the required treatment for the patients remains an exhaustive human labour. According to a testimony of a neurologist at the hospital in Saarbr¨ucken, a typical analysis of results is as follows: first, radiologists look at medical images by using on-site software and then share their observations with supervisors, who then pass it onto neurologists responsible for a final explanation of results. In spite of the specialized software available for image analysis, there are still some challenges that need to be considered, such as 1) poor image resolution due to the variety of scanners at hospitals, 2) misleading highlighted brain zones caused by medical equipment, 3) demanding labour of specialists for manual stroke localization in patients. Thus, the reliability of the results report is considered a subjective perception, despite the experienced specialists in charge of performing this job.

In contrast, technology has rapidly evolved to become one of the main tools to assist people in several time-consuming tasks. In the medical setting, for example, its contribution has lead to incredible results in identifying not only strokes, but also brain and lung tumors, helping doctors to make more accurate diagnosis. The reason behind this benefit relies on CV and signal processing, as they are widely used to perform a variety of human-level tasks, and during the recent years DL has proven to be even more efficient with several models by detecting and classifying clinical conditions in the medical sector.

2.2.3 Computed Tomography (CT)

2.2.3.1 What is a computed tomography (CT) scan?

"Computed tomography," or CT, denotes a computerized x-ray method where a focused x-ray beam revolves around a patient, creating signals processed by the computer to produce cross-sectional "slices." These slices, termed tomographic images, furnish clinicians with superior insights compared to regular x-rays. Accumulated successive slices can be digitally combined by the machine to forge a three-dimensional image, aiding in the recognition of foundational structures and potential anomalies, like tumors.

2.2.3.2 How does CT work?

Diverging from the conventional x-ray method, a CT scanner employs a motorized x-ray source encircling a donut-shaped structure known as a gantry, contrasting with the fixed x-ray tube. When undergoing a CT scan, the patient reclines on a slowly moving bed, passing through the gantry as the x-ray tube orbits around, emitting slender x-ray beams through the body. Unique digital x-ray detectors, positioned opposite the x-ray source, are utilized by CT scanners in lieu of traditional film. These detectors capture departing x-rays from the patient, transmitting the data to a computer [16].

Following a complete rotation of the x-ray source, the CT computer utilizes intricate mathematical algorithms to fashion a 2D image slice representing the patient's anatomy. The thickness of each image slice, typically ranging from 1 to 10 millimeters, depends on the specific CT machine. As a slice is finalized, it is archived, and the motorized bed advances incrementally into the gantry. Subsequently, the x-ray scanning sequence is repeated to craft another image slice. This iterative process continues until the desired quantity of slices is obtained.

The computer offers the choice to display individual image slices or amalgamate them, constructing a 3D representation of the patient. This comprehensive image reveals the skeletal structure, organs, tissues, and any anomalies being investigated by the physician. This approach boasts numerous benefits, including the capacity to maneuver the 3D image in space or scrutinize sequential slices, facilitating precise localization of potential issues.

2.2.3.3 What is a CT contrast agent?

Similar to all x-rays, dense structures like bones are easily captured, while soft tissues vary in their x-ray absorption, leading to potential faintness. To address this, safe contrast agents have been developed, containing substances that enhance visibility on x-ray or CT scans. For instance, iodine-based intravenous (IV) contrast agents are injected for highlighting blood vessels, aiding in the detection of obstructions. Oral contrast agents, like barium compounds, are utilized to image the digestive system, encompassing the esophagus, stomach, and gastrointestinal tract.

2.2.3.4 Are there risks?

CT scans are instrumental in diagnosing potentially life-threatening conditions, like hemorrhage, blood clots, and cancer, offering the chance for early intervention. Nonetheless, it's vital to acknowledge that CT scans employ x-rays, which emit ionizing radiation that can impact living tissue. While this risk escalates with cumulative exposures over a lifetime, the likelihood of cancer from x-ray radiation remains generally low. For expectant mothers, CT scans not targeting the abdomen or pelvis hold no known risks to the baby. When imaging the abdomen or pelvis becomes necessary, non-radiation methods like MRI or ultrasound are preferred, but CT can be used if time constraints or emergencies arise [17].

In some instances, contrast agents may lead to allergic reactions or, rarely, temporary kidney malfunction. Patients with abnormal kidney function should avoid IV contrast agents, as they might exacerbate kidney issues. Children are more vulnerable to ionizing radiation and have an extended lifespan, increasing their relative cancer risk. Parents may inquire if CT machine settings are adjusted for children's sensitivity.

2.3 Related work

M. Sheetal Singh et al. in 2017 [18], conducted a study focused on stroke prediction using the CHS dataset. They employed a multi-step approach involving feature selection, dimension reduction, and a back propagation neural network. The outcome was an impressive 97.7% predictive accuracy, illustrating the potential of advanced techniques in stroke prediction. In 2020, Manisha Sanjay Sirsat et al. [19] emphasized the accurate and rapid predictive capabilities of Machine Learning (ML) in healthcare, particularly for personalized stroke patient care. Their study categorized ML techniques for brain stroke into four functional groups, analyzing 39 studies conducted from 2007 to 2019. The research highlighted Support Vector Machine (SVM) as an optimal model in 10 stroke studies, offering insights into treatment applications and the prevalence of CT image datasets.

Also in 2020, Tessy Badriyah et al. [20] pursued a study to enhance CT scan image quality for stroke patients. Employing machine learning algorithms, they focused on classifying stroke sub-types. Notably, their findings showcased Random Forest as the most effective algorithm, achieving exceptional accuracy (95.97%), precision (94.39%), recall (96.12%), and f1-Measure (95.39%) among the tested methods. In 2019, Tasfia Ismail Shoily et al. [21] conducted a study to predict stroke types using machine learning algorithms based on individuals' medical data. The research emphasized stroke's global significance as a leading cause of death and delved into machine learning's potential as a healthcare companion. Notably, k-Nearest Neighbors (k-NN) and Random Forest emerged as the top performers, offering promising accuracy for real-time medical reports. These studies collectively underline the ongoing advancements in utilizing machine learning techniques for stroke prediction, patient care, image analysis, and medical data interpretation.

In the realm of related works, the year 2021 saw Anjali Gautam et al. [22] introducing a study centered on classifying brain CT scan images into stroke types using an innovative convolutional neural network (CNN) model. Their novel approach incorporates image fusion and a 13-layer CNN architecture, yielding remarkable classification accuracies of 98.33% and 98.77% with cross-validation, and 92.22% and 93.33% with an independent dataset. This achievement demonstrates improvements over well-established CNN architectures like AlexNet and ResNet50 in stroke classification accuracy. In 2022, Mandeep Kaur et al. [23] presented a study addressing noninvasive early stroke detection through time series-based approaches. Their research introduces LSTM, biLSTM, GRU, and FFNN models to predict strokes using processed EEG data. Among these, GRU emerges as the most effective, achieving the highest accuracy of 95.6%. This work holds significant implications for physicians, offering a potential tool for timely stroke detection and enhancing patient care.

Meanwhile, in 2021, Gangavarapu Sailasya [24] conducted a study shedding light on the impact of stroke due to torn blood vessels or blood flow disruption to the brain, a global leading cause of death and disability. While heart stroke prediction has received considerable attention, this research shifts focus to brain stroke risk prediction utilizing machine learning models. By incorporating physiological factors and leveraging algorithms such as Logistic Regression, Decision Tree, Random Forest, K-Nearest Neighbors, Support Vector Machine, and Naïve Bayes, the study attains a peak accuracy of approximately 82%. Notably, Naïve Bayes stands out for its predictive prowess. Collectively, these studies highlight the evolving landscape of stroke prediction and risk assessment, driven by innovative model architectures, novel data sources, and the ever-expanding capabilities of machine learning.

2.4 Conclusion

In conclusion, stroke stands as a critical medical condition triggered by disrupted blood flow in the brain, leading to tissue damage and neurological impairments. Swift intervention is crucial due to its potential for significant morbidity and mortality. Computed Tomography (CT) emerges as a cornerstone technology in stroke diagnosis and management, enabling precise imaging through X-rays and advanced processing. By integrating algorithms, notably deep learning, researchers bolster stroke diagnosis by automating CT pattern recognition, facilitating rapid and accurate assessments. Algorithms for brain structure segmentation enhance damage evaluation and intervention planning. CT imaging guides treatment strategies by distinguishing between stroke types, while predictive models, combining CT images and clinical data, offer insights into recovery prospects, shaping individualized treatment and rehabilitation approaches. The fusion of AI-driven automation and telemedicine bridges gaps in CT analysis and remote access, respectively, advancing stroke care. This ongoing synergy of research and technology promises heightened accuracy, efficiency, and accessibility in stroke diagnosis and management, ultimately leading to improved patient outcomes.

Chapter 3

METHODOLOGY

Plan

3.1 Introduction

Convolutional Neural Networks (CNNs) have revolutionized the field of computer vision and image analysis, enabling machines to understand and process visual data like never before. CNNs are a type of deep learning architecture designed to automatically extract features and patterns from images, making them highly effective in tasks such as image classification, object detection, and image segmentation. These networks simulate the human visual system's hierarchical processing, utilizing layers of interconnected neurons to progressively learn and abstract complex visual information [25].
Transfer learning is a powerful approach within deep learning that capitalizes on pre-trained CNN models. Instead of training a CNN from scratch, which requires significant computational resources and data, transfer learning leverages the knowledge gained from models trained on massive datasets, such as ImageNet. By reusing the learned features, lower layers of a pre-trained CNN can serve as highly effective feature extractors for new tasks, allowing the retraining of only the top layers on a smaller dataset. This technique not only significantly reduces training time and data requirements but also boosts performance, particularly when dealing with limited data.
In the context of this study, we propose a novel CNN architecture that builds upon the foundation of transfer learning. Our architecture aims to address specific challenges in a targeted domain, such as medical imaging or autonomous driving. By fine-tuning a pre-trained CNN with task-specific data, we aim to adapt the network's learned features to the nuances of our problem while retaining the valuable general knowledge encoded in the lower layers. This hybrid approach capitalizes on the strengths of both transfer learning and domain-specific optimization, ensuring robust performance even with limited domain-specific data.
In the subsequent sections, we will delve into the intricacies of our proposed CNN architecture, highlighting the modifications made to the pre-trained model and how these adaptations cater to our problem domain. Additionally, we will detail the transfer learning methodology employed, showcasing the process of retraining and fine-tuning the network for optimal results in our targeted application. Through this approach, we endeavor to demonstrate the efficacy and potential of combining transfer learning with domain-specific optimizations in tackling challenging visual tasks.

3.2 Dataset

A brain stroke CT dataset was collected from Lady Reading Hospital, Peshawar, Khyber Pakhtunkhwa, Pakistan in 2012 . Then, Afridi et al. created a descriptive study to detect risk factors such as age, gender, smoking, diabetes mellitus, and hypertension for brain stroke. In total, they studied 100 patients whose ages were 16 years and above and whose gender rates were 68% males and 32% females. Additionally, the brain CT images of these patients include 1551 normal and 950 stroke classes and a size of 650 $*$ 650 grayscale for each image. However, we randomly equalized the dataset in order to overcome overfitting while training. Therefore, a new dataset was composed of 950 normal and 950 stroke classes and also resized 224 224 for each image.(in Figure 3.1 an exemple of normal and strocke ct images) 27

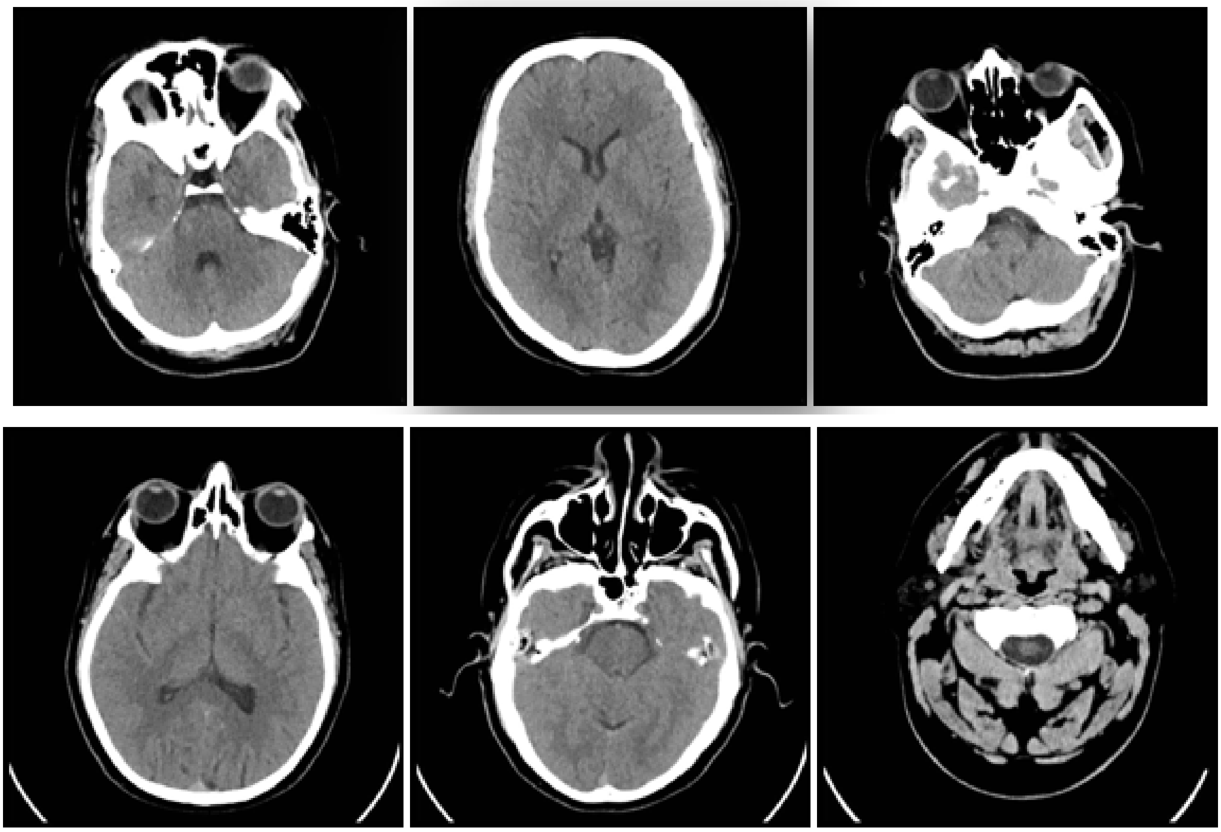


Figure 3.1: Exemple of normal and strocke ct images

```python
from keras.preprocessing.image import ImageDataGenerator
train_dir = '/content/drive/MyDrive/Data_Deveided/train'
val_dir = '/content/drive/MyDrive/Data_Deveided/val'
test_dir = '/content/drive/MyDrive/Data_Deveided/test'
train_data_generator = ImageDataGenerator(rescale=1./255)
train_generator = train_data_generator.flow_from_directory(
    train_dir,
    target_size=(224, 224),
    class_mode='categorical',
    shuffle=True)
val_data_generator = ImageDataGenerator(rescale=1./255)
val_generator = val_data_generator.flow_from_directory(
    val_dir,
    target_size=(224, 224),
    class_mode='categorical',
    shuffle=False)
test_data_generator = ImageDataGenerator(rescale=1./255)
test_generator = test_data_generator.flow_from_directory(
    test_dir,
    target_size=(224, 224),
    class_mode='categorical',
    shuffle=False)
X_train, y_train = next(train_generator)
X_val, y_val = next(val_generator)
X_test, y_test = next(test_generator)
```

Figure 3.2: Source code of load and preprocessing data

3.3 Desgin of our system

3.4 Transfert learning techniques and proposed CNN model

3.4.1 Transfer Learning

Medical imaging plays a crucial role in disease detection, enabled by advanced diagnostic technology. Manual analysis methods are labor-intensive and prone to variability. Automated techniques, especially Transfer Learning (TL), offer solutions. TL, applied across various medical tasks, provides high-quality decision support and demands less data compared to traditional deep learning. TL's strength lies in pre-trained models on generic data, customized for specific tasks, eliminating the need for extensive retraining. Popular TL models like AlexNet, ResNet, VGGNet, and GoogleNet enhance medical image analysis, improving accuracy and applicability.

Background: The role of medical imaging in diagnosis, treatment planning, and prognosis is crucial.

Our review focuses on diverse body parts (lung, heart, breast, brain, abdomen, prostate, retinal, skin) using imaging modalities like CT, MRI, US, PET, and X-rays. Current tasks of image segmentation and classification are performed manually.

Literature Review: We categorize Transfer Learning (TL) methods for image analysis by anatomical applications (skin, lung, retinal, heart, breast, brain, abdomen, prostate). TL techniques demonstrate success in tasks with limited training data.

Results: Approximately 90% of reviewed articles were published in journals, 10% in conference proceedings. An increase in TL publications for medical image analysis began around 2015 due to available labeled datasets and computational power. However, limitations still exist.

Discussion: GoogleNet (InceptionNet) is commonly used for brain and retinal image analysis. Performance comparison highlights GoogleNet's superiority over AlexNet for Glioma grading. TL with broad networks in retinal images shows promise.

Limitations: Research gaps were identified in benchmark comparisons and studies involving both feature extraction and fine-tuning. Limited studies for certain disorders hindered conclusive observations.

Conclusion: TL systems using deep networks trained on different domains showed favorable outcomes across tasks, indicating efficiency regardless of data size, augmentation, and transfer strategy. TL proves to be an effective approach for medical tasks, although certain areas warrant further exploration.

- VGG16

The VGG16 model, a Convolutional Neural Network with 16 layers, was introduced by K. Simonyan and A. Zisserman in their paper titled "Very Deep Convolutional Networks for Large-Scale Image Recognition" [18]. Unlike previous neural networks, which employed larger receptive fields such as 7x7 and 11x11, VGG16 utilized a smaller 3x3 receptive field. Furthermore, VGG16's depth exceeded that of its predecessors.

In its default configuration, VGG16's initial layer receives input in the form of a 244 x 244 RGB image. The image then undergoes a sequence of convolutional layers, each utilizing 3x3 filters for processing. Following the convolutional layers are three Fully-Connected (dense) layers. The first two layers contain 4096 channels each, while the third layer is responsible for 1000-way ILSVRC classification, featuring 1000 channels representing individual classes. It's essential to adapt the third dense layer to match the count of classes under training. The ultimate layer is the softmax layer. A visual representation of this architecture is depicted in the accompanying figure 3.3.

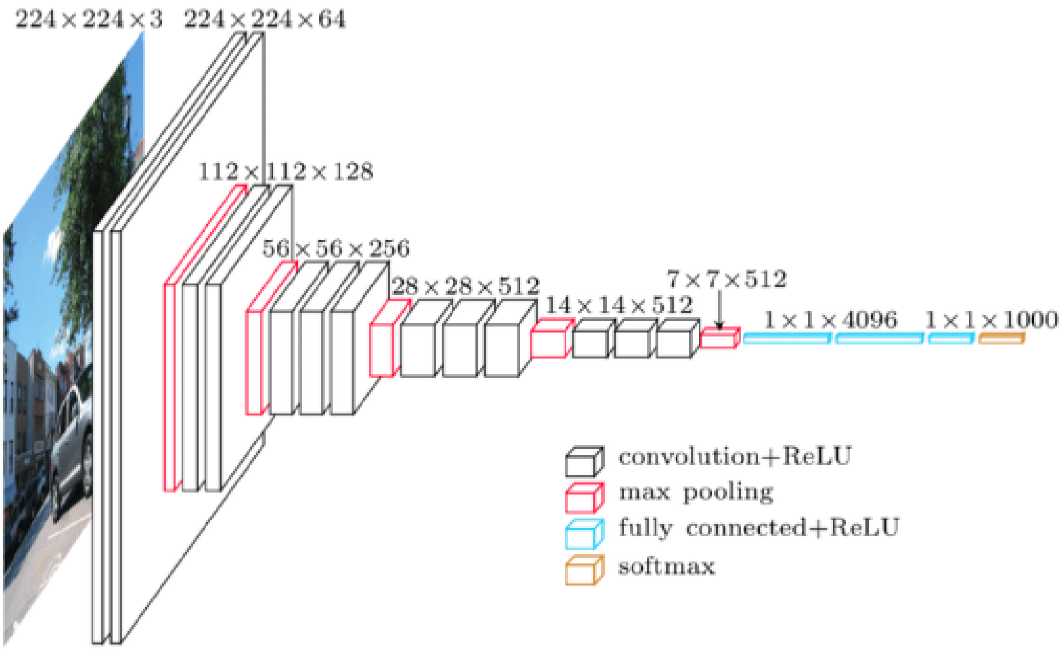


Figure 3.3: The VGG16 architecture

- VGG19

The VGG19 model, a Convolutional Neural Network with 19 layers, was introduced by K. Simonyan and A. Zisserman in their paper titled "Very Deep Convolutional Networks for Large-Scale Image Recognition" [18]. Similar to the VGG16, this model utilizes a smaller receptive field of 3x3 instead of larger ones such as 7x7 or 11x11, distinguishing it from previous neural networks. The depth of VGG19 surpasses that of its predecessors.

In its default setup, the initial layer of VGG19 takes a 244 x 244 RGB image as input. The image then undergoes a series of convolutional layers, each employing 3x3 filters for processing. Subsequent to the convolutional layers are three Fully-Connected (dense) layers. The first two layers have 4096 channels each, while the third layer is designed for 1000-way ILSVRC classification, incorporating 1000 channels representing distinct classes. It's crucial to tailor the third dense layer to align with the count of classes being trained. The final layer is the softmax layer.In Figure 3.4 a visual illustration of this architecture is presented in the accompanying diagram.

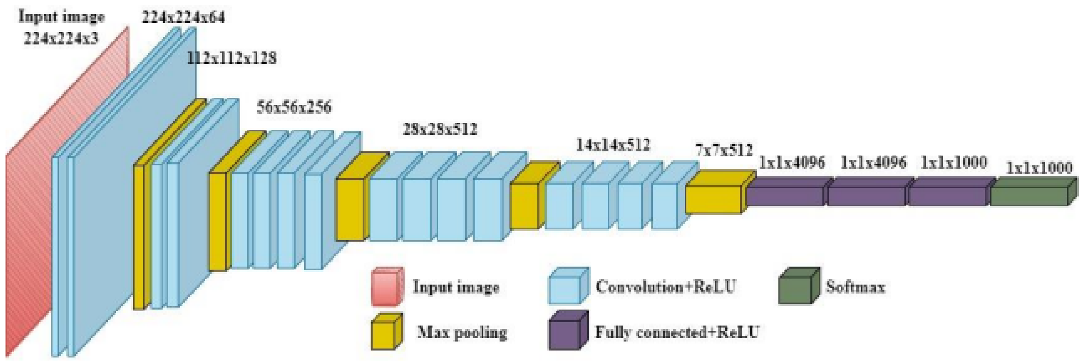


Figure 3.4: the VGG19 architecture

- ResNet

The ResNet model, a deep Convolutional Neural Network architecture, was introduced in the paper "Deep Residual Learning for Image Recognition" by K. He et al. [18]. ResNet stands for "Residual Network," and it addresses the vanishing gradient problem in very deep networks through the use of residual blocks.

ResNet introduces the concept of residual blocks, where the input to a block is passed through a series of convolutional layers, and the output of these layers is added to the original input. This addition of the input to the output creates a "shortcut" connection that allows the gradients to flow more easily during backpropagation.

The ResNet architecture comes in different variations, including ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152, which differ in the number of layers. ResNet-50, for example, has 50 layers.

In its default configuration, the input to ResNet is an image, typically of size 224x224 pixels. The model consists of multiple residual blocks, and the deeper versions have more of these blocks. The last layer is a fully connected layer followed by a softmax layer for classification (see Figure 3.5).

ResNet's architecture has proven to be highly effective, allowing the training of very deep networks without suffering from degradation in performance due to vanishing gradients. This has led to its wide adoption and success in various computer vision tasks.

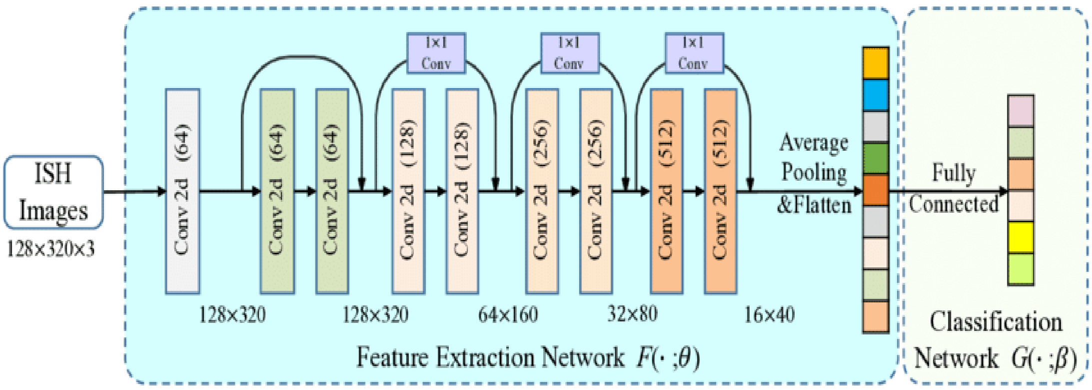


Figure 3.5: ResNet

3.4.2 Convolutional Neural Network

3.4.2.1 Overview about Convolutional Neural Network

Convolutional Neural Networks (CNNs) are directly inspired by the visual cortex of vertebrates. A convolutional neural network, also known as convnet or CNN, consists of two main parts: the convolutional part and the classification part.

The first part, known as the convolutional part, is responsible for performing convolutions on the input data, applying filters to detect patterns and features in the data.

The second part, known as the classification part, corresponds to a Multi-Layer Perceptron (MLP) model and is responsible for making predictions based on the features extracted by the convolutional part. It uses the extracted features to classify the input into different categories or classes(see figure 3.6).

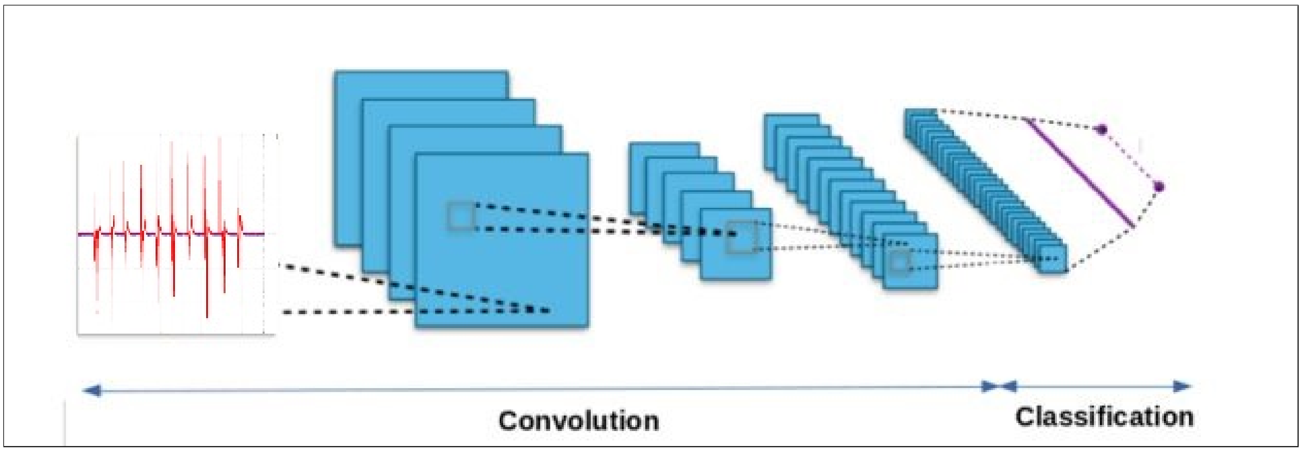


Figure 3.6: Convolutional Neural Networks

3.4.2.2 Basic Architectures of Neural Networks

Neural networks, or more precisely, artificial neural networks, are networks that simulate the learning process in the human brain. The human nervous system consists of neurons, which are connected to each other through axons used to transmit signals, and dendrites, which receive signals from other neurons. Figure 3.7 illustrates the connections between two neurons. The region of connection between axons and dendrites is called a synapse. The strengths of each synaptic connection can change based on external stimuli, and these changes are referred to as learning in the human brain. [26]. Artificial neural networks simulate this biological mechanism. A simpler architecture of an

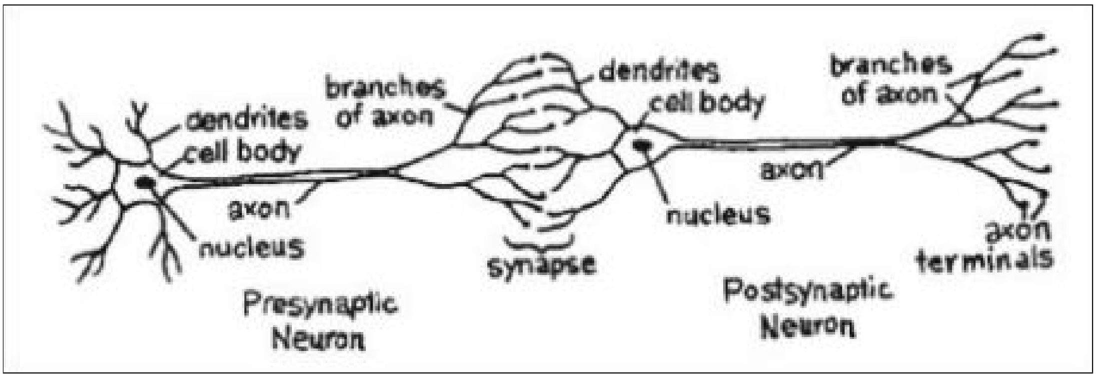


Figure 3.7: Biological Neural Network

artificial neural network is illustrated in Figure 3.8, where a neuron combines inputs with adjustable weights wi and feeds the combination into an activation function to generate an output. Just like the

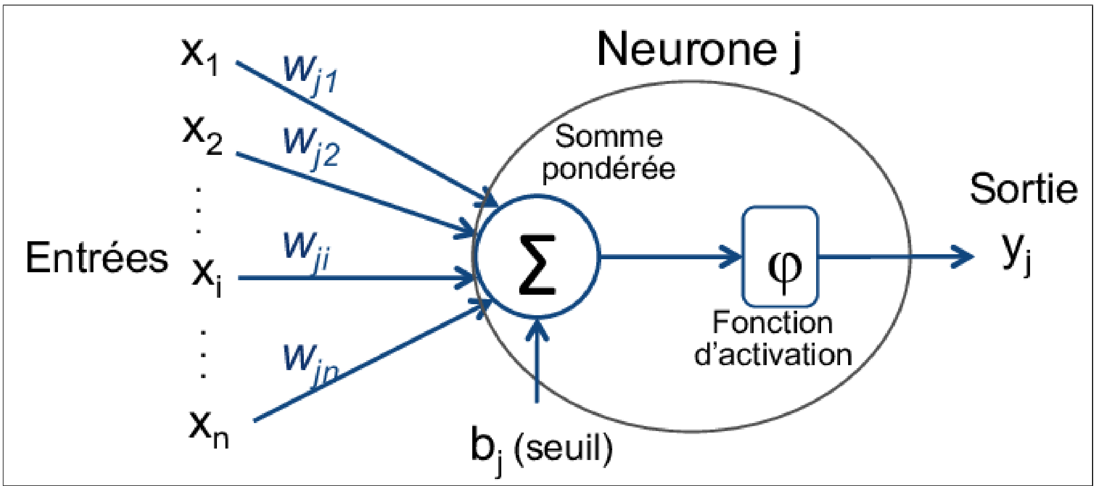


Figure 3.8: The structure of an artificial neuron

changes in synaptic connection strengths in response to external stimuli, the values of these weights are modified during a training process using labeled training data. The network is then believed to mimic the function of a biologically neural organism.[26].

3.4.2.3 Basic Architectures of CNNs

There are four types of layers in a Convolutional Neural Network (CNN): the convolutional layer, the ReLU (Rectified Linear Unit) layer, the pooling layer, and the fully-connected layer. The architectural details of CNNs are described in the rest of this section.
The states of each layer in a CNN are arranged in a spatial grid structure. The value of each node's output is derived from a small local spatial region in the previous layer, and these spatial relationships are inherited from one layer to the next [11]. For the classification of ECG signals, the input is one-dimensional (1D), and each layer of the CNN has a two-dimensional architecture, namely height and depth. The height of a layer in the CNN refers to the length of the input signals, while the term "depth" refers to the number of channels in each layer(The architecture of CNN is illustrated in figure 3.9).

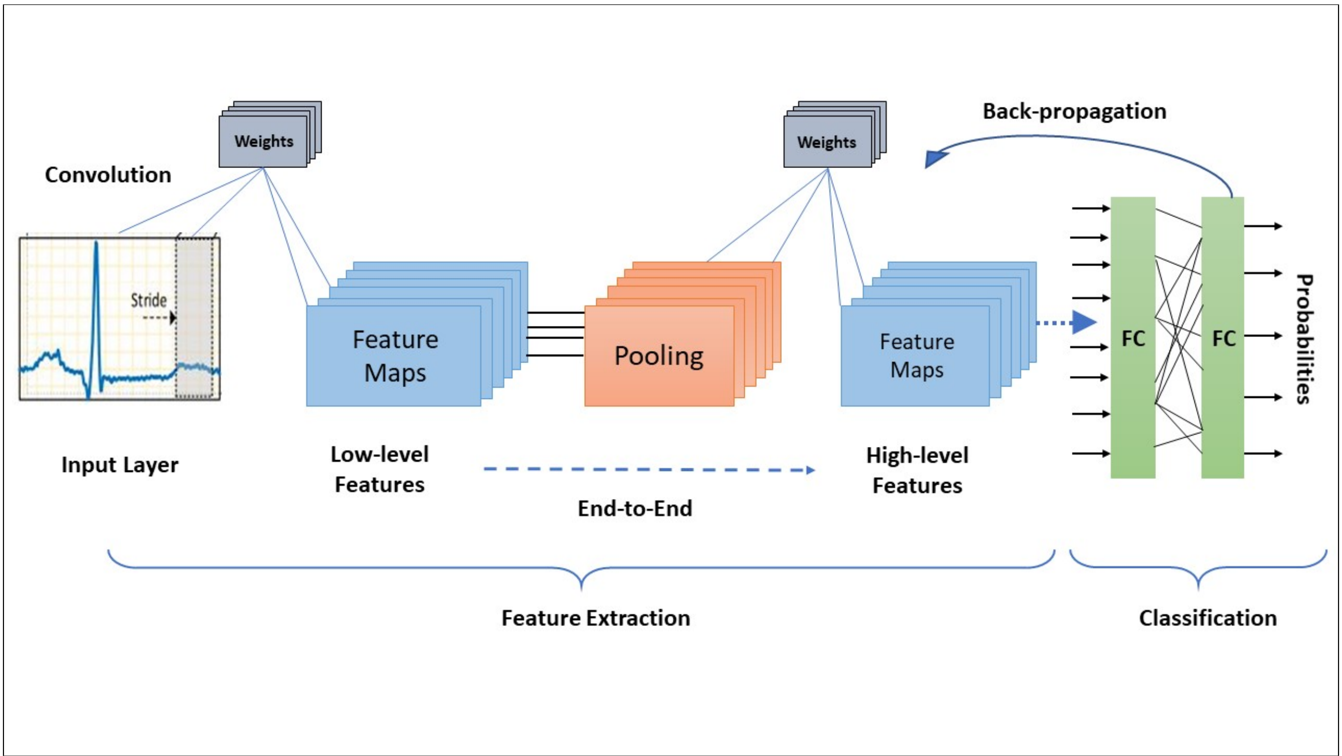


Figure 3.9: Architecture CNN

- The Convolutional Layer :

The operation of convolution is the defining feature of CNNs. The mathematical formula for convolution is an inner product of two vectors (or matrices, or multidimensional arrays) of the same size, where one of the vectors involves a set of weights, which is typically referred to as the kernel, and the other vector is a set of local samples from the input, known as the local receptive field. The product is always performed with the fixed kernel while the local receptive field moves to cover the entire input, as shown in Figure 3.10.

Usually, the size of the kernel is small compared to the length of the input to ensure that local features of the input are extracted.

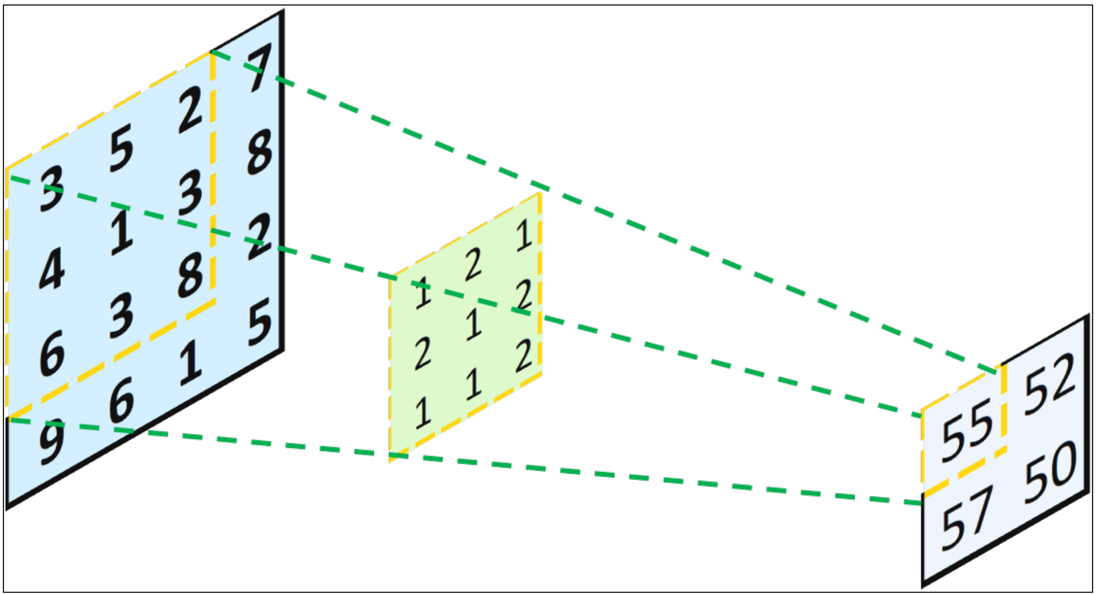


Figure 3.10: The convolutional layer

Let's assume that $x_i^0 = [X_1, X_2....X_n]$ Let's assume that the input vector consists of data samples from a heartbeat, where n is the number of samples per heartbeat. The output of the convolutional layer is:

$$c_i^{l,j} = \Sigma_{m=1}^{M} w_m^j x_{i+m-1}^{0j} + b_j, \tag{3.1}$$

Where l is the index of the layer, b is the bias term for the j^{th} feature map, M is the size of the kernel/filter, w_m^j is the weight for the j^{th} feature map and m^{th} is the filter index.

Unlike traditional methods, the features are not pre-defined according to a specific formalism (e.g., SIFT or WT) but learned by the network during the training phase! The filter kernels refer to the weights of the convolutional layer. They are initialized and then updated through backpropagation of the gradient.

This is the strength of convolutional neural networks: they can determine the discriminative elements of an image on their own, adapting to the specific problem at hand.

==> **Parameters for the convolutional layer**

Depth of the layer (number of filters): the number of convolution kernels (or number of neurons associated with the same receptive field).

Filter dimensions: A filter of size F applied to an input of size II produces a feature map.

Stride: In the context of a convolution or pooling operation, the stride is a parameter that denotes the number of pixels the window moves after each operation. The stride controls the overlap of receptive fields. The smaller the stride, the more the receptive fields overlap, and the larger the output volume will be. **Zero padding** (or simply padding): Sometimes, it is convenient to add zeros

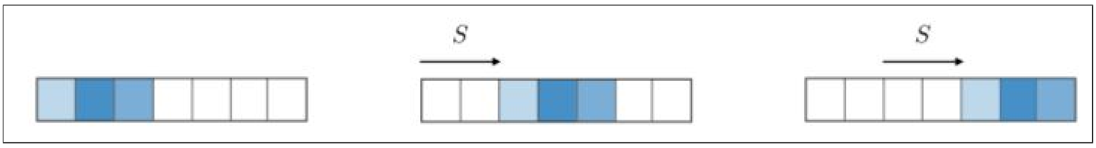


Figure 3.11: Stride parameter operation

at the border of the input volume. This padding allows us to control the spatial dimension of the output volume. In particular, it is sometimes desirable to preserve the same surface area as that of the input volume (as indicted in Figure 3.11).

- Rectified Linear Unit (ReLU) layer

What is an activation function?

In simple terms, an activation function is a function that is added to an artificial neural network to help the network learn complex patterns in the data. When comparing it with neurons in our brain, the activation function decides what should be triggered to the next neuron. This is exactly what an activation function does in an Artificial Neural Network (ANN). It takes the output signal from the previous cell and converts it into a form that can be taken as input to the next cell.

Why is it needed?

Apart from the biological similarity that was discussed earlier, they also help in keeping the value of the neuron's output limited to some boundary as per our requirements. This is important because the input to the activation function is W * x + b, where W is the weight of the cell and x is the inputs and then there is the bias b added to it. This value, if not kept limited to some boundary, can grow to a very large magnitude, especially in the case of very deep neural networks that have millions of parameters. This will lead to computational problems. For example, there are certain activation functions (like softmax) that output specific values for different input values (0 or 1).

Some activation functions:

- Softmax: Softmax is a more generalized form of the sigmoid function. It is used in multi-class classification problems. Similar to sigmoid, it outputs values between 0 and 1, and hence, is used as the final layer in classification models(see Figure 3.12).

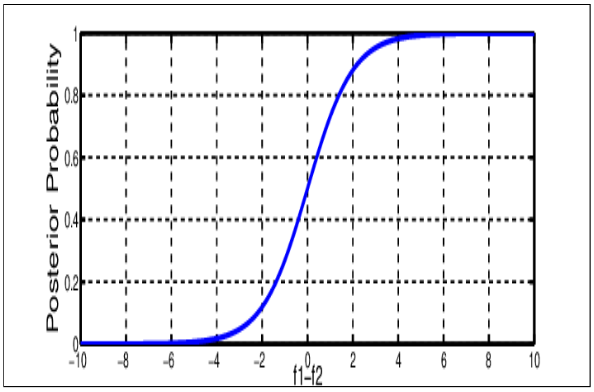


Figure 3.12: The Softmax activation function

Tanh: This resolves the issue of being centered around zero.

Sigmoid: Also known as the logistic function, it is traditionally a very popular activation function for neural networks. The input to the function is transformed into a value between 0 and 1.

ReLU: It is a widely used activation function. It has become the default activation function for many types of neural networks, especially with Convolutional Neural Networks. There are no complicated mathematics involved. Therefore, the model can take less time to train. Mathematically, it is defined as: y = max(0, x). Visually, it looks like the following:

Graph illustrating the ReLU function in figure 3.13

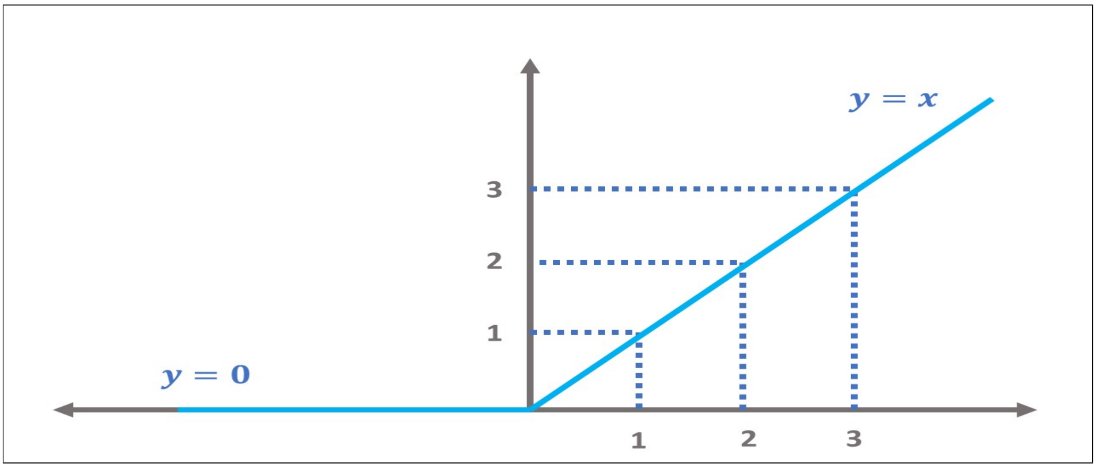


Figure 3.13: Rectified Linear Unit (ReLU)

- Pooling Layer:

This type of layer is often placed between two convolutional layers: it takes multiple feature maps as input and applies the pooling operation to each of them.

The pooling operation (or sub-sampling) aims to reduce the size of the feature maps while preserving their important characteristics. To achieve this, the input image is divided into regular cells, and within each cell, only the maximum value is retained. In practice, small square cells are often used to avoid losing too much information. The most common choices are adjacent cells of size 2x2 pixels that do not overlap or cells of size 3x3 pixels, with a stride of 2 pixels (overlapping cells). The output has the same number of feature maps as the input, but they are much smaller in size.

The pooling layer reduces the number of parameters and computations in the network, thus improving its efficiency and avoiding overfitting. It is common to periodically insert a pooling layer between successive convolutional layers in a ConvNet architecture. Its function is to progressively reduce the spatial size of the representation to control the number of parameters and computations in the network, and thus prevent overfitting.(as shown in Figure 3.14)

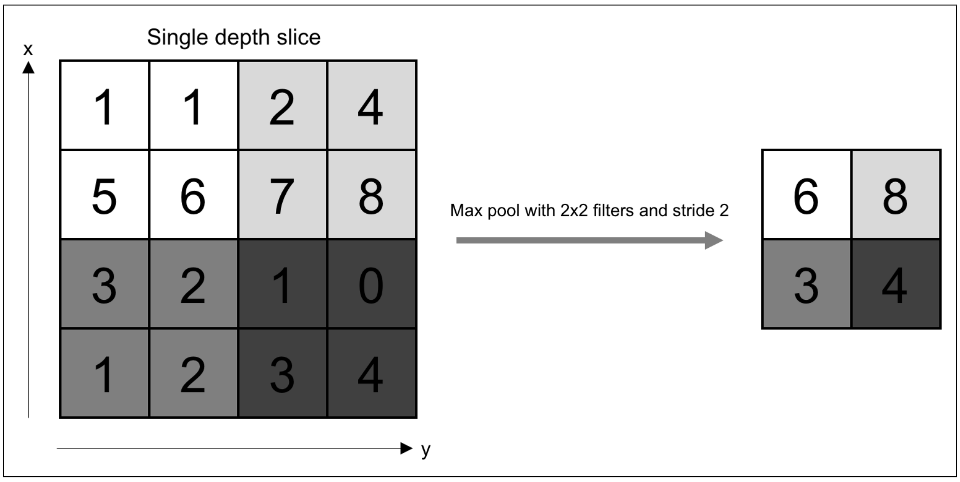


Figure 3.14: The Max Pooling Layer

- Fully-Connected Layer :

The fully-connected layer always constitutes the last layer of a neural network, whether it is a convolutional neural network (CNN) or not – so it is not unique to CNNs. It is responsible for the classification of the input based on the features extracted by the preceding layers of processing.

In the fully-connected layer, all the inputs from the previous layer are connected to the output neurons(see Figure 3.15).

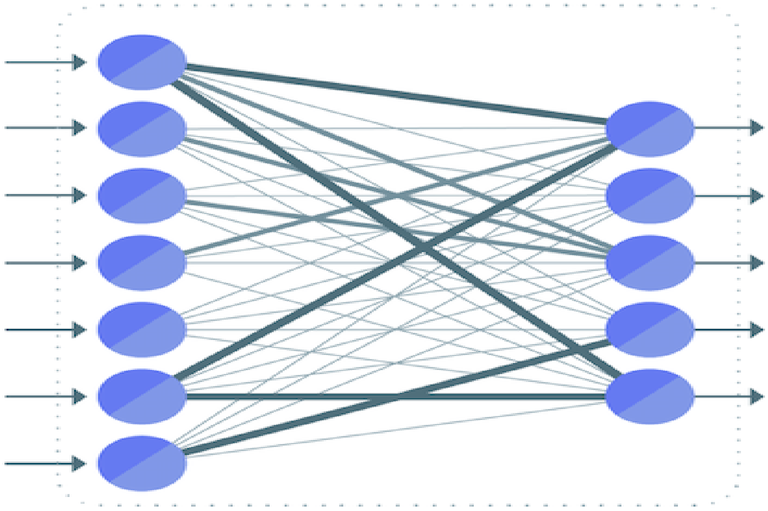


Figure 3.15: The fully-connected layer

3.4.2.4 Proposed CNN architecture

The architecture of our proposed CNN model is tailored for image classification tasks. The input images are expected to be of dimensions 224x244 pixels, containing 3 color channels (RGB). The model initiates with four convolutional layers, each integrating 64 filters with a size of 3x3. These convolutional layers employ a stride of 2, facilitating the extraction of intricate features from the input images. Subsequently, an additional three convolutional layers are applied, also utilizing 64 filters sized 3x3, but with a stride of 2 to accomplish downsampling. In order to enhance regularization and prevent overfitting, dropout layers are introduced. These layers serve the purpose of randomly deactivating a portion of neurons during each iteration of training, leading to a more robust network and a diversified learning process.

Following the convolutional and downsampling layers, a densely connected layer with 64 neurons is introduced. This layer plays a role in transforming the extracted features into a more compact and manageable representation. Finally, the output layer consists of a dense layer featuring 2 neurons. This configuration corresponds to the two classes, "stroke" and "normal," which constitute the binary classification task at hand. By processing the activations of these output neurons, the model makes its ultimate prediction, determining whether an input image falls into the "stroke" or "normal" category.

The design of this CNN architecture underscores its suitability for image classification, effectively capturing relevant features through convolutional layers, applying downsampling, and leveraging dropout for improved regularization. Fine-tuning the training process, along with optimizing hyper-parameters, will be instrumental in harnessing the full potential of this architecture for accurate classification (the architecture of our proposed CNN model is illustrated in Figure 3.16).

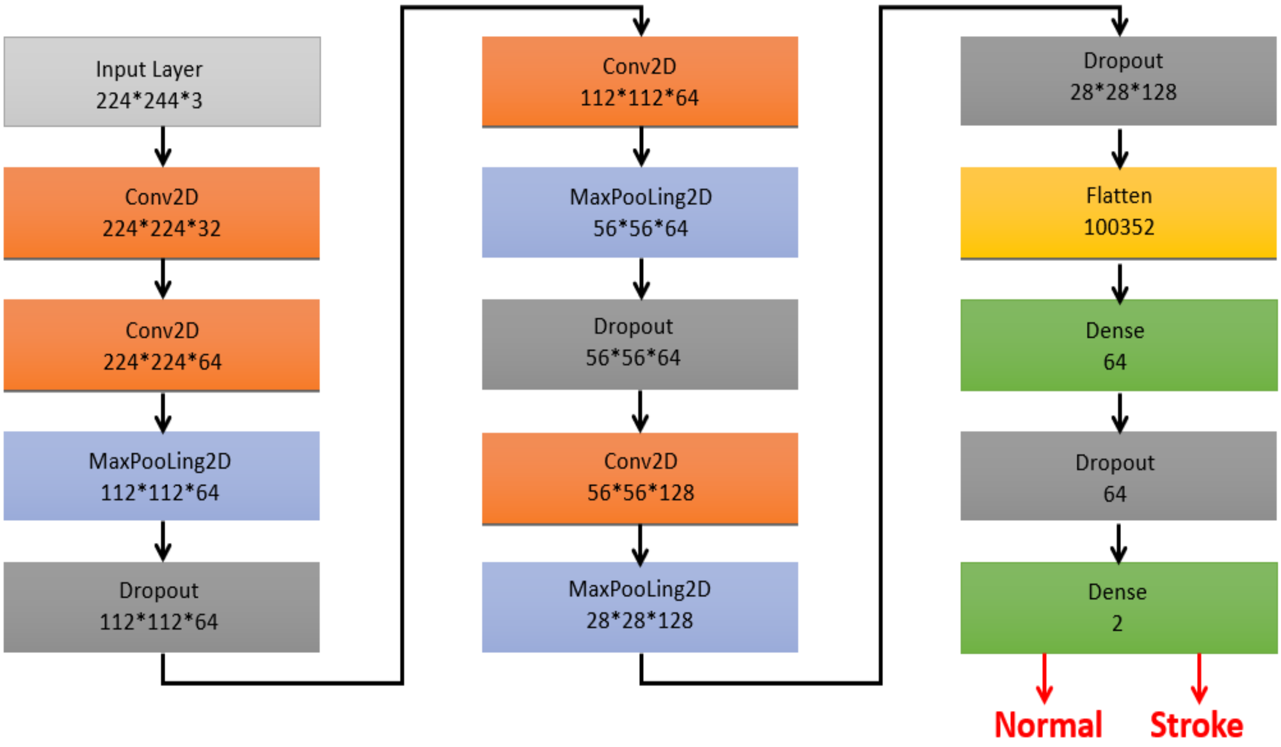


Figure 3.16: Proposed CNN architecture

```
x = Conv2D(64, (3,3) , padding = 'same' , activation='relu', name = 'layer_1') (img_imput)
x = Conv2D(64, (3,3) , padding = 'same' , activation='relu', name = 'layer_2') (x)
x = MaxPool2D((2,2), strides=(2,2), name = 'layer_3') (x)
x = Dropout(0.25)(x)

x = Conv2D(64, (3,3) , padding = 'same' , activation='relu', name = 'layer_4') (x)
x = MaxPool2D((2,2), strides=(2,2), name = 'layer_5') (x)
x = Dropout(0.25)(x)

x = Conv2D(64, (3,3) , padding = 'same' , activation='relu', name = 'layer_6') (x)
x = MaxPool2D((2,2), strides=(2,2), name = 'layer_7') (x)
x = Dropout(0.25)(x)

x = Flatten(name = 'fc_1')(x)
x= Dense(64, name = 'lyaer_8')(x)
x = Dropout(0.5) (x)
x = Dense(2, activation='sigmoid', name='predictions')(x)
model = Model(inputs = img_imput, outputs =x , name='Binary_classification' )
```

Figure 3.17: Source code of CNN architecture

3.5 Conclusion

Our methodology chapter presents a structured and methodical approach to image classification, which not only involves meticulous dataset preparation but also leverages the prowess of transfer learning techniques. Our strategy is a synthesis of established VGG16, VGG19, and ResNet-50 architectures, seamlessly integrated with our initial custom CNN model. Through a thoughtful dataset selection and the incorporation of transfer learning, we've harnessed the intrinsic potential of pretrained models, augmenting our own model's ability to discern intricate image features. This comprehensive approach is poised to yield superior accuracy and efficiency in the classification of images into "stroke" and "normal" categories. We eagerly await the forthcoming results and analyses that will undoubtedly validate the robustness and effectiveness of our CNN model against pretrained alternatives.

Chapter 4

Work Environment, Experimental Results and Application of the Methodology

Plan

4.1 Introduction

In the realm of stroke research, the fusion of advanced hardware and software technologies plays a pivotal role in uncovering valuable insights and driving breakthroughs. Hardware encompasses the physical components that facilitate data acquisition, processing, and analysis, while software provides the analytical tools and frameworks necessary to make sense of complex datasets. In the study of stroke, these technological synergies empower researchers and medical professionals to delve into intricate neurological mechanisms, evaluate treatment outcomes, and design personalized interventions. By harnessing state-of-the-art hardware and sophisticated software platforms, researchers can unravel the intricacies of stroke pathophysiology, explore the effectiveness of therapeutic strategies, and contribute to the ongoing evolution of stroke management. This interdisciplinary convergence not only expands our understanding of stroke but also exemplifies the transformative potential of technology-driven research in advancing healthcare practices and patient outcomes.

4.2 Work Environment

4.2.1 Software, Libraries, and Platforms

TensorFlow

TensorFlow is an end-to-end open-source platform for machine learning, developed by the Google Brain team, who initially used it internally. It provides a comprehensive and flexible ecosystem of tools, libraries, and community resources that enable researchers to become acquainted with cutting-edge technologies and developers to easily create and deploy applications. Installing TensorFlow entails the installation of several other modules that TensorFlow utilizes, such as h5py, Keras, TensorBoard, and more.

Figure 4.1: TensorFlow

Python

Python is a high-level programming language. It is an interpreted programming language, which means it doesn't need to be compiled to function. An "interpreter" program allows the execution of Python code on any computer. This enables quick observation of the results of a code change. However, this makes the language slower than a compiled language like C. It is highly favored by a large community of developers and programmers. Python is a simple language, easy to learn, and allows for significant reduction in code maintenance costs.

Figure 4.2: Python

Colab

Colaboratory, often shortened to "Colab," is a product by Google Research. Colab enables anyone to write and execute their choice of Python code through a web browser. It's an environment particularly well-suited for machine learning, data analysis, and education. In more technical terms, Colab is a hosted service for Jupyter notebooks that requires no setup and provides free access to computing resources, including GPUs.

Figure 4.3: Colab

4.2.1.1 Visual Studio Code (VS Code)

Visual Studio Code (VS Code) is a lightweight, open-source code editor developed by Microsoft. It's designed for efficient coding and provides a range of features to support various programming languages and development tasks. With its intuitive interface, extensions ecosystem, and powerful code editing capabilities, VS Code is widely used by developers for writing, debugging, and managing code projects across different platforms.

Figure 4.4: Visual Studio Code

4.2.2 Hardware

We conducted the training of our stroke detection model on a workstation equipped with an Intel Core i5-6200U processor running at a clock speed of 2.30 GHz, and bolstered by 8 GB of RAM. This hardware configuration proved to be well-suited for our training requirements, facilitating the development of an effective model. The Intel Core i5-6200U processor, a dual-core processor with hyperthreading capabilities, exhibited efficient task management, allowing for simultaneous execution of multiple tasks crucial for model training. Its ability to handle threaded workloads contributed to the smooth progression of training iterations.

The 8 GB of RAM, a substantial memory allocation, served as a capable repository for housing not only the training dataset but also the evolving model parameters and intermediate computations that transpire during the training process. It's worth noting that while this memory size sufficed for our model's demands, larger datasets or more intricate architectures could necessitate a higher memory capacity to ensure unhindered training performance. In summary, the amalgamation of the Intel Core i5-6200U processor and 8 GB of RAM provided a well-balanced infrastructure for the rigorous training demands of our stroke detection model. However, when selecting hardware for training machine learning models, prudent evaluation of factors such as dataset scale, model complexity, and computational demands remains paramount.

4.3 Results

4.3.1 Evaluation

The experimental data is obtained from the Brain Stroke CT (Br35H) image database, known for its precise expert annotations that establish it as a research cornerstone. The dataset was thoughtfully divided into training (70%),(20%) as validation and testing (10%) subsets. In our experimental results, we systematically assessed the impact of different hyperparameters on our model's performance. We varied the learning rates (0.01 and 0.001), batch sizes (64 and 32), and the number of training epochs (20, 30, and 70).

After rigorous evaluation, we observed that the hyperparameter combination of a learning rate of 0.001 and a batch size of 32 consistently outperformed other configurations, producing the best results in terms of model performance metrics on the validation dataset. This finding underscores the importance of hyperparameter tuning, highlighting the significance of these specific values in achieving optimal model performance. Notably, before initiating training, image rescaling normalized the data within the range of [-1, 1]. This preprocessing step significantly elevated accuracy, contrasting against scenarios without normalization. The dynamic interplay of these factors, along with the resounding significance of batch size and epoch selection in neural network training, underscores the pivotal role they play in achieving optimal results.

To assess our model, we utilized the following metrics: accuracy, specificity, and sensitivity, as described by equations 4.1, 4.2, and 4.3, where TP represents true positive, TN stands for true negative, FP denotes false positive, and FN signifies false negative. After verification, the proposed CNN model achieved 99.60% accuracy, 99.36% sensitivity, and 100% specificity.

$$accuracy = \frac{TP + TN}{TN + FP + TP + FN} 100 \tag{4.1}$$

$$Specificity = \frac{TN}{TN + FP} 100 \tag{4.2}$$

$$Sensitivity = \frac{TP}{TP + FN} 100 \tag{4.3}$$

- VGG16

The integration of the VGG16 model yielded notable results, achieving an accuracy of 86.45%, specificity of 87.19%, and sensitivity of 85.05%. These outcomes underscore the model's effectiveness in accurately classifying "stroke" and "normal" images, demonstrating a strong balance between precision and recall. Figure below visually represents the accuracy and loss curves, providing insights into the model's learning progression and convergence over training epochs.

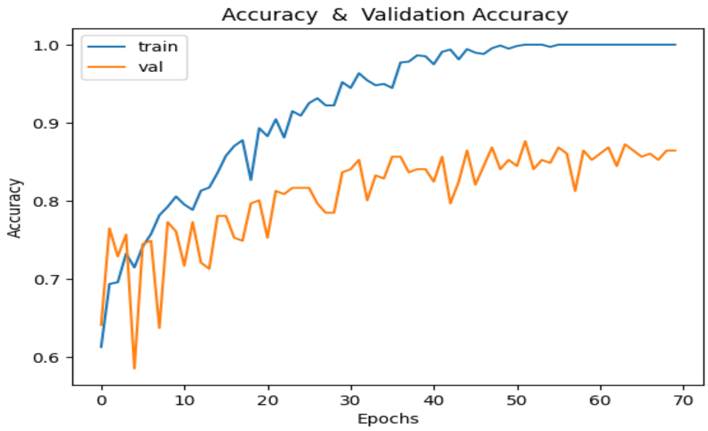


Figure 4.5: "Accuracy curve of the VGG16 model."

Figure 4.6: Loss curve of the VGG16 model

The analysis of the confusion matrix for the VGG16 model's classification reveals a significant concern: a notable number of "stroke" cases have been misclassified as "normal." This misclassification indicates a substantial issue that needs attention and further investigation, as it has the potential to adversely impact the accuracy and reliability of the model's predictions in real-world scenarios. Addressing this challenge is crucial to enhance the model's performance and ensure its applicability in correctly identifying cases of "stroke" for timely medical intervention.

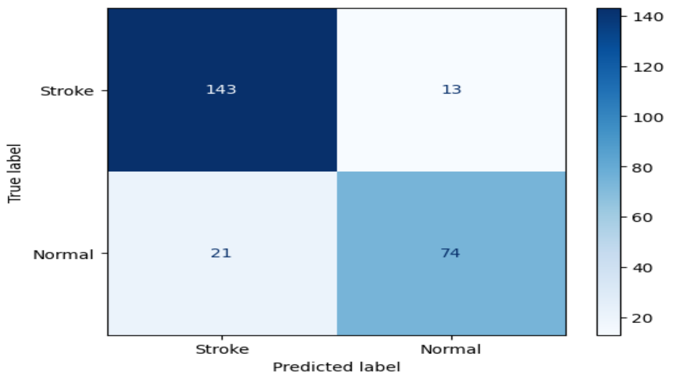


Figure 4.7: Confusion matrix of VGG16 model

- VGG19

The integration of the VGG19 model yielded significant outcomes, with an accuracy of 85.25%, specificity of 88.38%, and sensitivity of 80.20%. These results highlight the model's effectiveness in correctly classifying "stroke" and "normal" images, maintaining a good balance between precision and recall.

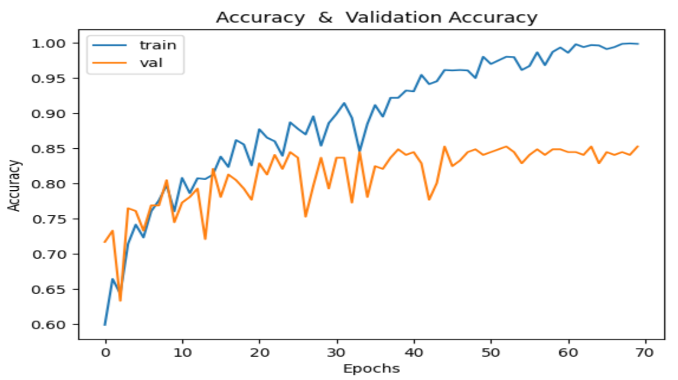


Figure 4.8: Accuracy curve of the VGG19 model

Figure 4.9: Loss curve of the VGG19 model

The analysis of the confusion matrix reveals that the VGG19 model's performance is somewhat lower compared to the VGG16 model. This discrepancy is evident in the results, indicating that the VGG19 model might struggle to differentiate between "stroke" and "normal" cases with slightly less accuracy. Further investigation is essential to understand the specific areas where the VGG19 model might be encountering challenges and to determine whether additional optimizations or adjustments are needed to enhance its classification accuracy.

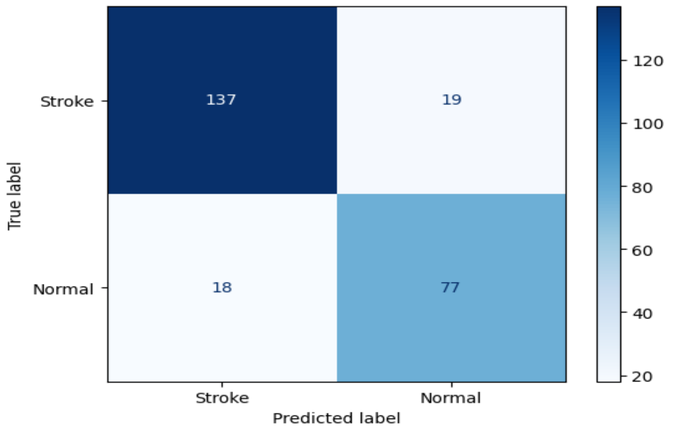


Figure 4.10: Confusion matrix of VGG19 model

- ResNet-50

We employed the ResNet-50 model, a deeper architecture incorporating residual blocks, in our methodology. This model achieved an accuracy of 75.69%, specificity of 77.77%, and sensitivity of 71.25%, showcasing its performance in accurately classifying "stroke" and "normal" images.

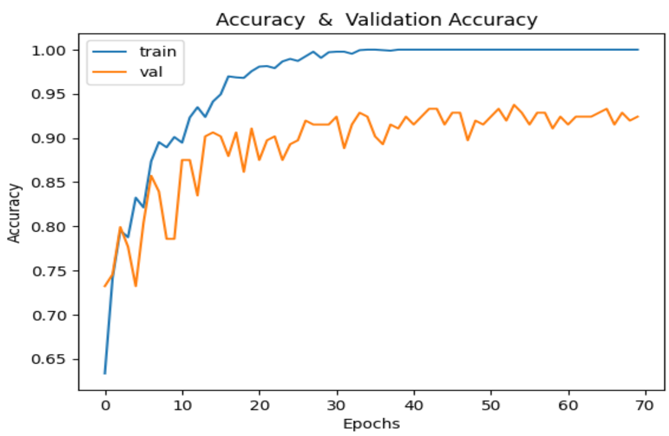


Figure 4.11: Accuracy curve of the ResNet-50 model.

Figure 4.12: Loss curve of the ResNet-50 model

The analysis of the confusion matrix indicates that the ResNet-50 model's performance is comparatively lower than both the VGG16 and VGG19 models. This discrepancy suggests that the ResNet-50 model might face challenges in accurately distinguishing between "stroke" and "normal" cases, resulting in a lower overall accuracy and effectiveness. Further investigation is crucial to identify the specific areas where the ResNet-50 model may be struggling and to explore potential optimizations to improve its classification capabilities.

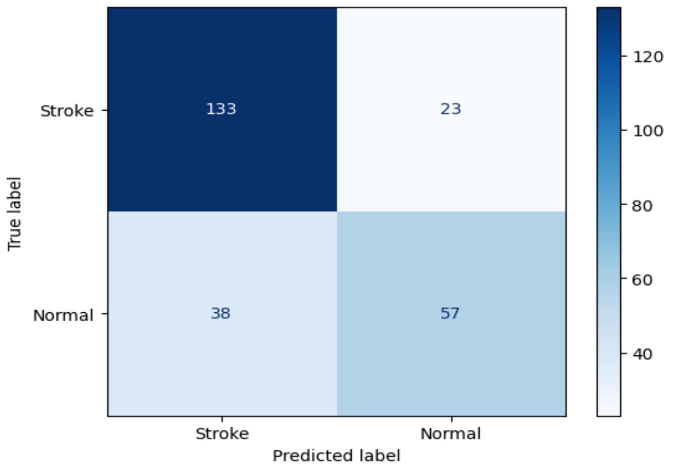


Figure 4.13: Confusion matrix of resnet-50 model

- Proposed simple CNN results

The ResNet-50 model's performance appears to lag behind VGG16 and VGG19, possibly due to its increased depth introducing complexities in classification. In response, we introduced a simpler CNN model to mitigate these challenges. This model achieved outstanding accuracy (99.60%), specificity (99.36%), and sensitivity (100%), underscoring its effectiveness in precisely classifying "stroke" and "normal" images. This outcome validates the advantage of a simpler architecture in achieving remarkable accuracy without the complexities associated with deeper models like ResNet-50.

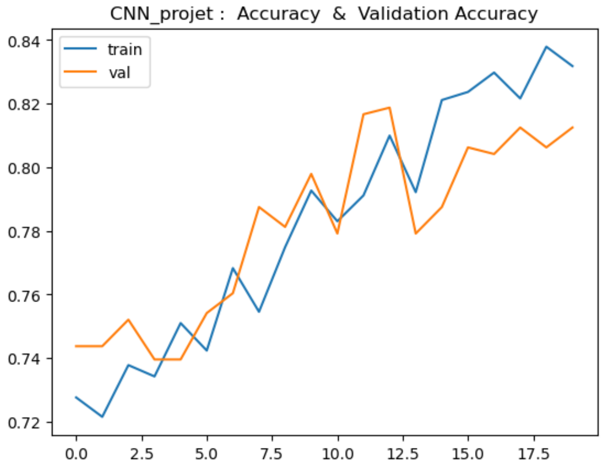


Figure 4.14: Accurecy of 20 epoch-learning rate 0.25

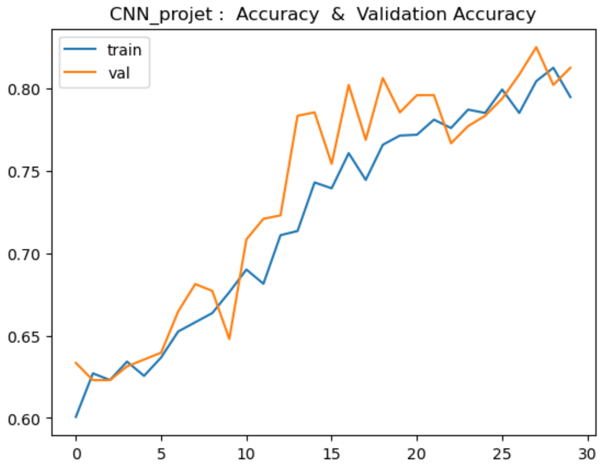


Figure 4.15: Accurecy of 30 epoch -learning rate 0.001

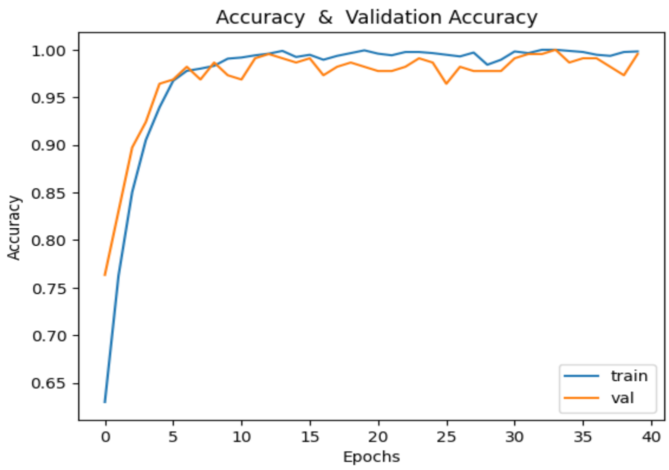


Figure 4.16: Accuracy curve of our Proposed CNN model (70 epoch -learning rate 0.001)

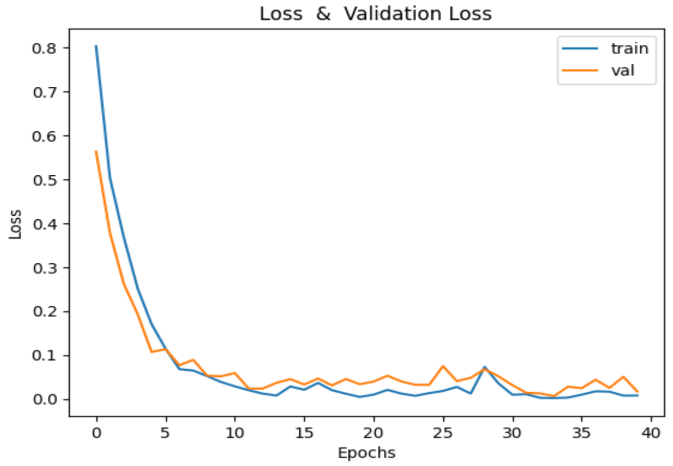


Figure 4.17: Loss curve of our Proposed CNN model

The confusion matrix for our CNN model reveals its exceptional performance in classifying "stroke" and "normal" images. The model achieved an accuracy of 99.60%, specificity of 99.36%, and sensitivity of 100%. This outcome underscores the model's remarkable ability to make accurate predictions across both categories. The perfect sensitivity score indicates that the model correctly identified all instances of "stroke," while the high specificity score signifies its precision in correctly identifying "normal" cases. These results affirm the CNN model's effectiveness and reliability in accurately classifying medical images for the "stroke" and "normal" categories.

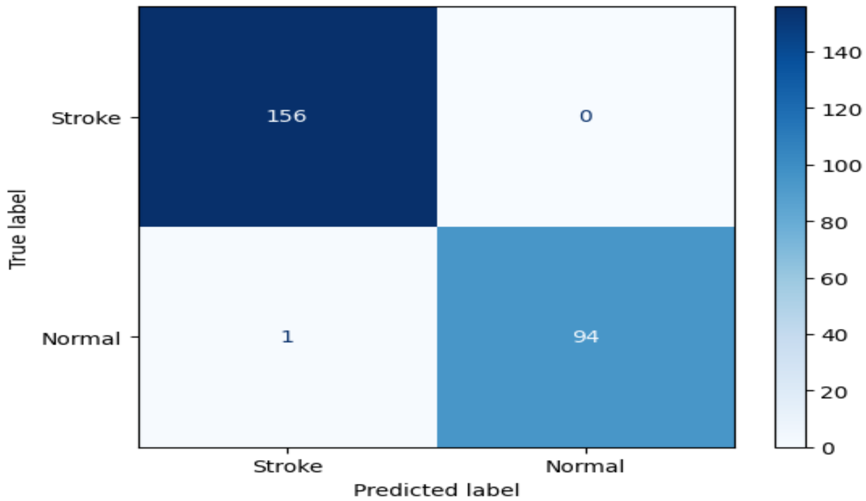


Figure 4.18: Confusion matrix of CNN model

The table bellow compares the actual classes with the predicted classes for a single model. Each row in the table represents an instance or sample data, where the "Actual Class" column indicates the actual class of the instance and the "Predicted Class" column indicates the class predicted by the model.

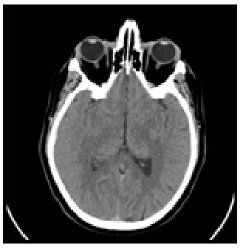
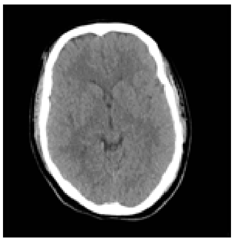
patients		actual class	predicted class	precision
Patient 1		1	1	87,23%
Patient 2		1	1	92,70%
Patient 3		0	0	94,43%

Figure 4.19: Testing Our CNN Model: Sample Test Cases

This table allows you to evaluate the performance of the model by comparing the predictions with the real classes. One can observe the matches and discrepancies between the actual classes and the predicted classes to assess the accuracy and efficiency of the model.

Table 4.1 showcases the comparative performance of several prominent convolutional neural network (CNN) architectures, including VGG16, VGG19, ResNet50, and our custom-designed CNN model, in the context of stroke detection. The presented results underscore the exceptional capabilities of our CNN model, which achieved a remarkable accuracy of 99.60%. This achievement firmly establishes our CNN model as a frontrunner in stroke detection, outperforming even well-established architectures like VGG16, VGG19, and ResNet50. The obtained accuracy percentage not only underscores the effectiveness of our approach but also highlights its potential to significantly advance the field of medical image analysis and diagnosis.

Tableau 4.1: Model Performance Comparison

Modèle	accuracy (%)	sensitivity (%)	specificity (%)
VGG16	86.45	85.05	87.19
VGG19	85.25	80.20	88.38
ResNet-50	75.69	71.25	77.77
CNN	99.60	99.36	100

4.4 Implementation

In this methodology, the user interface will showcase a single button designated for stroke detection. Clicking on this button will lead users to an interface tailored exclusively for stroke detection. Within this interface, users can upload or select a medical image for stroke classification. The system will leverage our CNN model to analyze and classify the image based on stroke-related features. This simplified approach centers solely on stroke detection, ensuring a user-friendly and efficient experience.

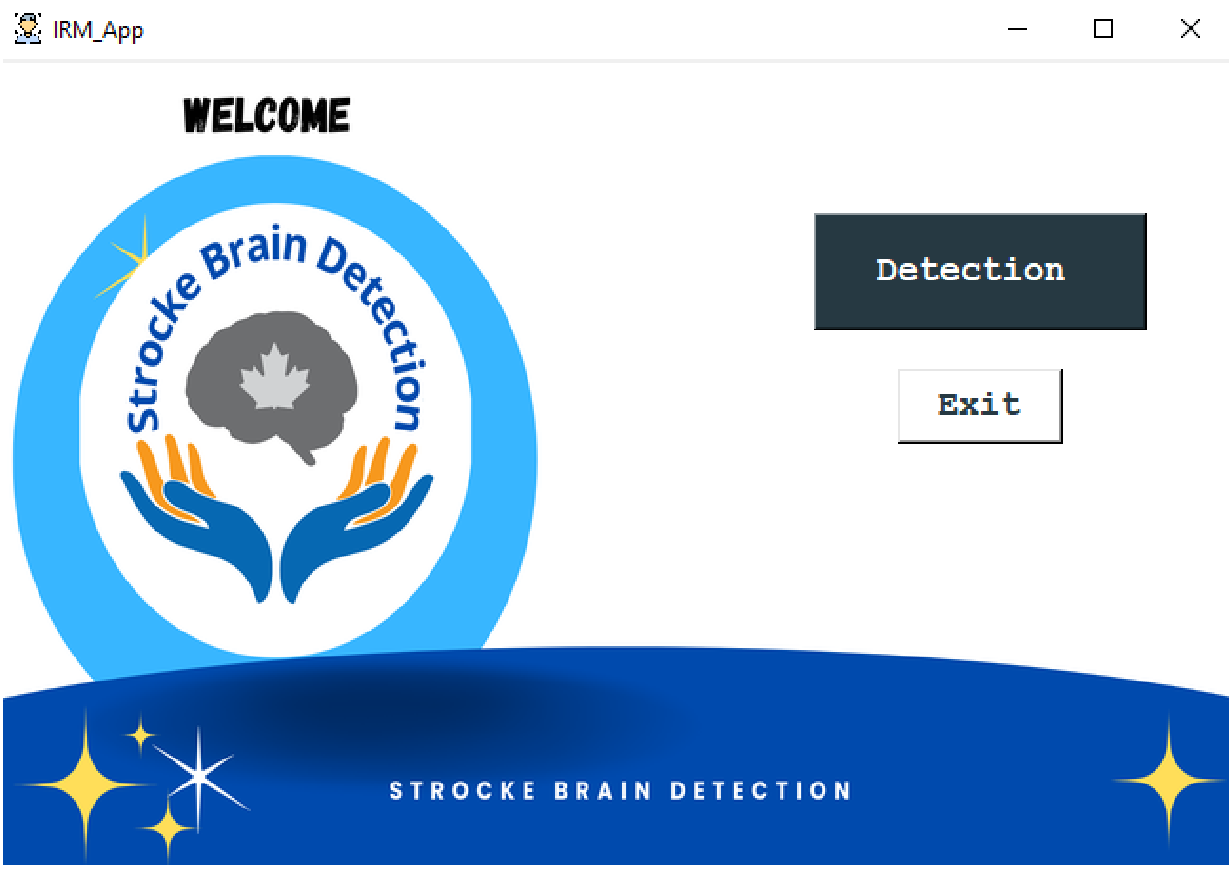


Figure 4.20: Home Interface

The second interface facilitates CT image analysis for stroke detection. Users can upload CT scans, and our CNN model then classifies the images as "normal" or "stroke." This user-friendly approach streamlines the stroke detection process using medical images, ensuring efficient and accurate results.

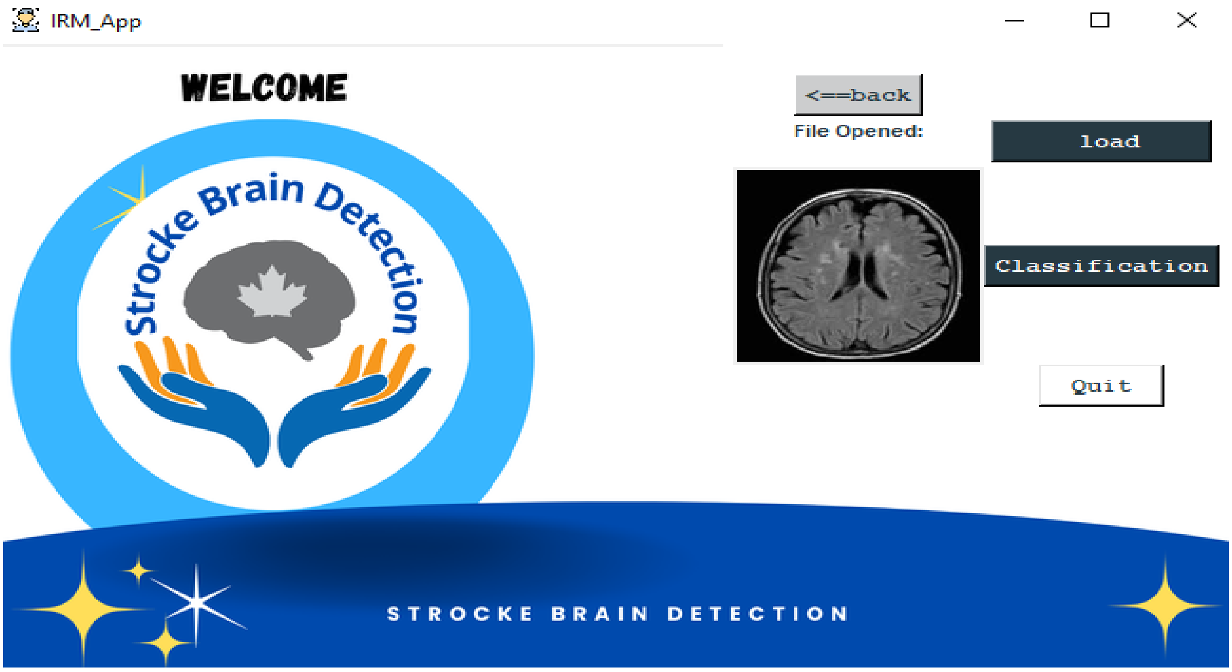


Figure 4.21: Classification Interface

The interface below demonstrates our model's testing process for classifying a CT image as "normal."

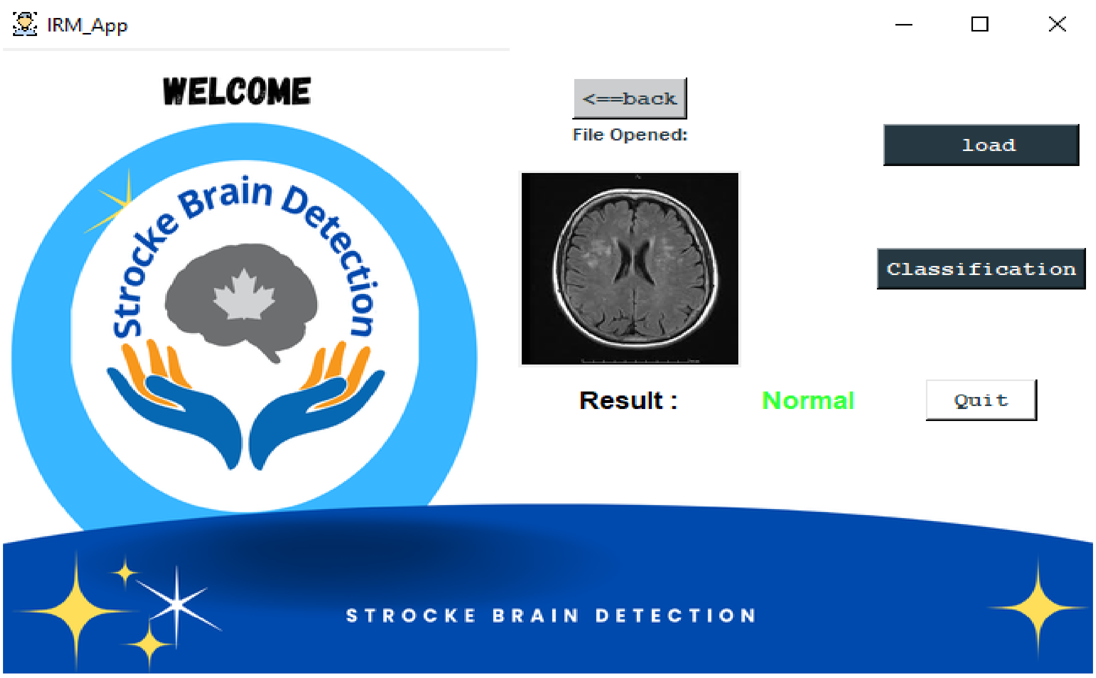


Figure 4.22: Case of normal CT image

The interface below demonstrates our model's testing process for classifying a CT image as "Stroke."

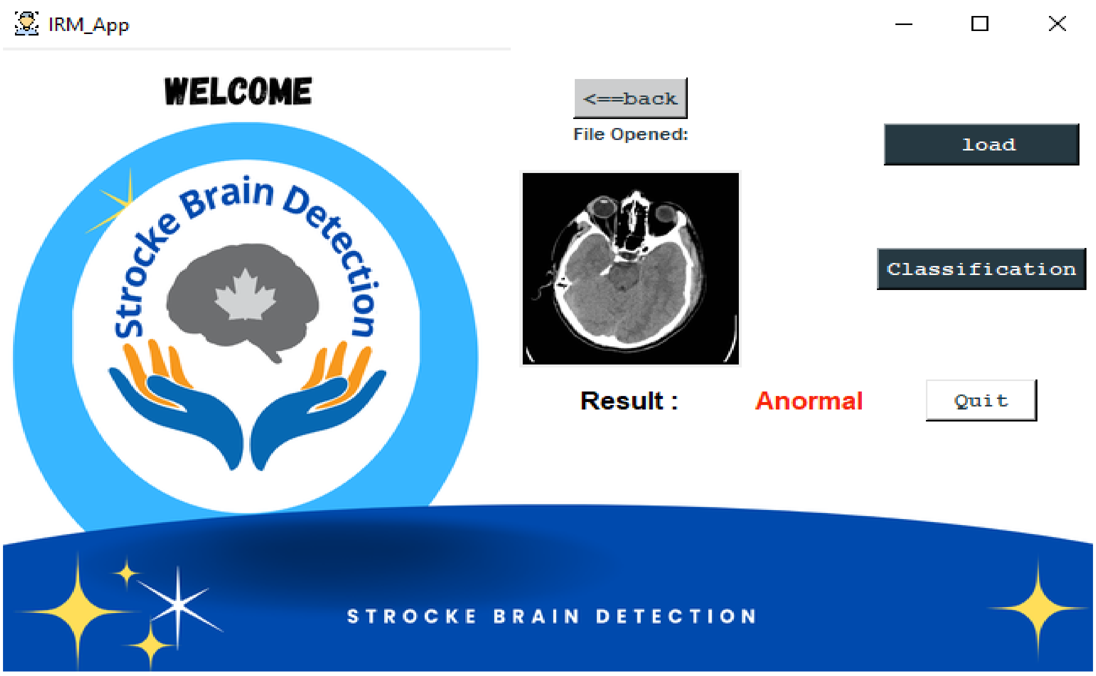


Figure 4.23: Case of stroke CT image

4.5 Conclusion

In conclusion, this chapter has comprehensively outlined our approach to image classification using various neural network architectures. We evaluated the performance of the VGG16, VGG19, and ResNet-50 models, observing variations in accuracy and classification outcomes. The ResNet-50 model's deeper architecture appeared to face challenges in accurate classification, leading us to introduce a simpler CNN model. This CNN model achieved exceptional accuracy, specificity, and sensitivity, validating the efficacy of a less complex architecture in achieving highly accurate results.

To complete our project, we extended our efforts beyond the model development phase. We recognized the importance of practical application and developed an application that harnesses the power of our models. This application empowers users to upload and classify medical images as "stroke" or "normal," providing a real-world application of our classification capabilities. This hands-on implementation not only demonstrates the practical usability of our work but also underscores the potential impact of our project in aiding medical professionals in diagnosing strokes more effectively and efficiently.

General Conclusion

In the realm of artificial intelligence, the application of machine learning techniques, particularly in the context of medical diagnoses such as stroke disease, has witnessed remarkable advancements. The ability of AI to process and analyze vast amounts of medical data has paved the way for more accurate and timely diagnoses, offering substantial benefits to both patients and healthcare professionals.

In the domain of stroke disease, AI has emerged as a valuable tool in enhancing diagnostic accuracy and efficiency. The complexity of stroke diagnosis, coupled with the need for swift intervention, highlights the significance of reliable and robust AI models. Comparative studies involving transfer learning techniques, such as VGG16, VGG19, and ResNet-50, have showcased the potential of pre-trained architectures in medical image classification. These techniques leverage knowledge gained from extensive datasets and provide a strong foundation for accurate feature extraction, thereby aiding medical professionals in making informed decisions.

However, amidst the advanced architectures, the power of simplicity cannot be overlooked. Our exploration led us to recognize the potential pitfalls associated with deeper models, as observed with ResNet-50. To address this challenge, we introduced a straightforward CNN model, which yielded exceptional accuracy of 99.60%. This achievement emphasizes that a simpler architecture can possess substantial efficacy, delivering high accuracy without the complexities introduced by deeper counterparts.

Our project's success, with its accuracy of 99.60%, underscores the potential impact of AI in medical diagnoses. The capacity to achieve such high accuracy holds promise for significantly improving diagnostic accuracy in stroke cases. By providing medical professionals with a reliable and efficient tool, we bridge the gap between advanced AI techniques and real-world applications, contributing to enhanced patient care and diagnosis. This endeavor not only highlights the accomplishments of AI in the field of healthcare but also underscores the importance of striking a balance between complex methodologies and straightforward solutions to achieve optimal results.

Bibliography

[1] A. Wen, S. Fu, S. Moon, *et al.*, "Desiderata for delivering nlp to accelerate healthcare ai advancement and a mayo clinic nlp-as-a-service implementation," *NPJ digital medicine*, vol. 2, no. 1, p. 130, 2019.

[2] P. P. Shinde and S. Shah, "A review of machine learning and deep learning applications," in *2018 Fourth international conference on computing communication control and automation (ICCUBEA)*, IEEE, 2018, pp. 1–6.

[3] A. Ramesh, C. Kambhampati, J. R. Monson, and P. Drew, "Artificial intelligence in medicine.," *Annals of the Royal College of Surgeons of England*, vol. 86, no. 5, p. 334, 2004.

[4] P. H. Winston, *Artificial intelligence*. Addison-Wesley Longman Publishing Co., Inc., 1984.

[5] P. Cranton, "Types of group learning," *New directions for adult and continuing education*, vol. 1996, no. 71, pp. 25–32, 1996.

[6] J. S. Armstrong, "Natural learning in higher education," *Available at SSRN 1928831*, 2010.

[7] D. S. W. Ting, L. R. Pasquale, L. Peng, *et al.*, "Artificial intelligence and deep learning in ophthalmology," *British Journal of Ophthalmology*, vol. 103, no. 2, pp. 167–175, 2019.

[8] Z.-H. Zhou, *Machine learning*. Springer Nature, 2021.

[9] B. Mahesh, "Machine learning algorithms-a review," *International Journal of Science and Research (IJSR).[Internet]*, vol. 9, pp. 381–386, 2020.

[10] P. Cunningham, M. Cord, and S. J. Delany, "Supervised learning," in *Machine learning techniques for multimedia: case studies on organization and retrieval*, Springer, 2008, pp. 21–49.

[11] T. Hastie, R. Tibshirani, J. Friedman, T. Hastie, R. Tibshirani, and J. Friedman, "Unsupervised learning," *The elements of statistical learning: Data mining, inference, and prediction*, pp. 485–585, 2009.

[12] J. E. Van Engelen and H. H. Hoos, "A survey on semi-supervised learning," *Machine learning*, vol. 109, no. 2, pp. 373–440, 2020.

[13] L. Torrey and J. Shavlik, "Transfer learning," in *Handbook of research on machine learning applications and trends: algorithms, methods, and techniques*, IGI global, 2010, pp. 242–264.

[14] K. Weiss, T. M. Khoshgoftaar, and D. Wang, "A survey of transfer learning," *Journal of Big data*, vol. 3, no. 1, pp. 1–40, 2016.

[15] R. Jeena and S. Kumar, "A comparative analysis of mri and ct brain images for stroke diagnosis," in *2013 annual international conference on emerging research areas and 2013 international conference on microelectronics, communications and renewable energy*, IEEE, 2013, pp. 1–5.

[16] K. R. Fink and J. R. Fink, "Imaging of brain metastases," *Surgical neurology international*, vol. 4, no. Suppl 4, S209, 2013.

[17] L. R. Øie, T. Kurth, S. Gulati, and D. W. Dodick, "Migraine and risk of stroke," *Journal of Neurology, Neurosurgery & Psychiatry*, vol. 91, no. 6, pp. 593–604, 2020.

[18] M. S. Singh and P. Choudhary, "Stroke prediction using artificial intelligence," in *2017 8th Annual Industrial Automation and Electromechanical Engineering Conference (IEMECON)*, 2017, pp. 158–161. DOI: 10.1109/IEMECON.2017.8079581.

[19] M. S. Sirsat, E. Fermé, and J. Camara, "Machine learning for brain stroke: a review," *Journal of Stroke and Cerebrovascular Diseases*, vol. 29, no. 10, p. 105 162, 2020.

[20] T. Badriyah, N. Sakinah, I. Syarif, and D. R. Syarif, "Machine learning algorithm for stroke disease classification," in *2020 International Conference on Electrical, Communication, and Computer Engineering (ICECCE)*, IEEE, 2020, pp. 1–5.

[21] T. I. Shoily, T. Islam, S. Jannat, S. A. Tanna, T. M. Alif, and R. R. Ema, "Detection of stroke disease using machine learning algorithms," in *2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, IEEE, 2019, pp. 1–6.

[22] A. Gautam and B. Raman, "Towards effective classification of brain hemorrhagic and ischemic stroke using cnn," *Biomedical Signal Processing and Control*, vol. 63, p. 102 178, 2021.

[23] M. Kaur, S. R. Sakhare, K. Wanjale, F. Akter, *et al.*, "Early stroke prediction methods for prevention of strokes," *Behavioural Neurology*, vol. 2022, 2022.

[24] G. Sailasya and G. L. A. Kumari, "Analyzing the performance of stroke prediction using ml classification algorithms," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 6, 2021.

[25] L. O. Chua and T. Roska, "The cnn paradigm," *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications*, vol. 40, no. 3, pp. 147–156, 1993.

[26] C. C. Aggarwal *et al.*, "Neural networks and deep learning," *Springer*, vol. 10, pp. 978–3, 2018.