N° d'ordre :
N° de série :

PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA
Ministry of Higher Education and Scientific Research

UNIVERSITY OF ECHAHID HAMMA LAKHDAR - EL OUED

FACULTY OF EXACT SCIENCES
Computer Science Department

Mémoire de fin d'étude

ACADEMIC MASTER

Field: **Mathematics and Computer Science**
Option: **Computer Science**
Specialty: **Distributed Systems and Artificial Intelligence**

Presented by :

- **Taabli Dounia**
- **Hadjaidji Kawther**

Title

Development of Barefoot trace recognition system

Defended on June 16 th 2022

Examination Commitee :

M.	……………………	MCA		Chair
M.	……………………	MAA		Examinator
Dr.	ZAIZ Faouzi	MCB	El-oued university	Supervisor

Academic year : 2021-2022

Dedication

Praise and thanks are only for Allah, the One who, by His blessing and favor, perfected works and deeds are accomplished.
All Praise be to God, who has bestowed upon us the grace of health and wellness.
Without him, this humble work could not be completed. Having said that :
To the one who is suffering day after day, so that we may acquire the best knowledge and rise in its ranks. My dear father. May you continue to be my treasure and a crown upon my head.
To the one who spent sleepless nights praying and supplicating; my mother, who gave us care and tenderness.
To my brothers who have supported me throughout my journey: Bilal, Elheythem, Houssam Eddine, Ayman, and Imade Eddine.
To my sisters : Hadjer and roumaissa.
To the children of our family: Samer, Nizar, bachayer, and Rahaf.
To my grandmother, my maternal and paternal uncles, and aunts.
To my friends : Roumaissa, Intissar, Kawther, Aya, Chaima, Samira, Badra, Rania, Meriem, Hanan, Khadija, Manar,... and the list is long.
To my friends: Akram, Mohamed, my colleague, and my cousin Noufel.
To the pure souls, we lost but their shadows have never gone from home, my tender grandmother and grandfather.
For everyone who was by my side, and helped me from near or far, even with a kind word
. To my professors and to everyone who taught me a letter, to the Department of Computer Science in particular, and the entire University of Mohammed Lakhdar.
Thank God.
Dounia Taabli.

Dedication

To the owner of a fragrant biography and enlightened thought, for he had the first credit in attaining higher education (my beloved father), may God prolong his life.
To those who set me on the path of life, made me calm, and took care of me until I became old (my mother).
To the inexhaustible love for good without limits, with whom I shared my life, to whom they are the bond, my brothers and sisters.
To those who were the bond of joy, to those with whom I shared moments, to my dearest friends: Dounia, Aya, Samira, Badra, Chaima, Rania, Manar ...
To my classmates who have been of help to me: M, A, Y, Z, A.F, N,...
To all my dear professors, who did not hesitate to extend a helping hand to me.
Thank God.
Hadjaidji Kawther .

Acknowledgements

Above all, I thank Almighty God for the good health and courage He has given us to prepare for this humble work. And yet.
*We thank the honorable professor,**Mr.Zaiz Faouzi** , who accepted us to lead us thanks to his criticisms, comments, and directions.*
*I also extend my thanks and appreciation to **Mr.Guarbi Kaddour** : for agreeing to chair the jury, and I also thank **Ms.Belila Khaoula** : who honored me by accepting my judgment.*
We thank all those who directly or indirectly contributed to the success of this research, especially the parents who helped us throughout our lives until today, without forgetting, of course, all the technical and administrative supervision of Hama Lakhdar University in the Valley.

Résumé

Dans le passé, la science du suivi était connue sous le nom de qayyafa, dans laquelle un expert bédouin déduit des informations vitales sur une personne à partir de ses empreintes. De plus, la reconnaissance humaine est l'un des domaines les plus populaires de la vision par ordinateur. L'identification biométrique utilisant le bout du doigt ou l'iris, ou l'empreinte digitale, est la méthode la plus prometteuse actuellement étudiée à cette fin. Parce que les empreintes des pieds n'ont pas de propriétés biométriques, il est beaucoup plus difficile d'identifier les personnes qui les utilisent que d'utiliser des empreintes de pieds. L'objectif de ce projet est de transformer la procédure de « qayyafa » en un système intelligent. À l'aide des techniques de traitement d'image, le système extrait les caractéristiques de suivi du pied à partir de l'image d'entrée. Des approches avancées d'apprentissage en profondeur sont utilisées pour aider à détecter les traces et identifier rapidement les attributs de chaque trace. Nous utilisons une approche de réseau neuronal convolutionnel dans le système proposé pour estimer le propriétaire du pied en fonction des attributs dérivés du système mis en œuvre.

Pour cet objectif, nous avons proposé un système, où nous formerons un réseau neuronal convolutif qui prédit l'âge et le sexe à partir d'une image contenant l'empreinte digitale d'une personne en utilisant un modèle CNN pour extraire les caractéristiques de l'image. Le modèle se compose de deux parties, un modèle pré-formé et classifié. Le modèle VGG16 pré-entraîné a été choisit pour être intégré dans un système de classification (Softmax).

Les résultats obtenus montrent clairement une bonne précision de 96.5%, mais reste insuffisant pour résoudre l'aspect de la reconnaissance de traces pieds nus. De plus, certains aspects pourraient être améliorés.

Mots-clés : traitement d'images, réseau de neurones convolutifs, couche Softmax, VGG16, modèle pré-entraîné, foot tracking, barefoot tracking, classification de modèles binaires, classification multi-modèles.

Abstract

In the past, tracking science was known as 'Al-Qiyafah' science, in which an expert nomad deduce vital information about a person from its footprints. In addition, one of the most popular fields in computer vision is human identification. Biometric identification using the finger or iris, or a footprint scan, is the most promising method currently being researched for this purpose. Because foot traces lack biometric characteristics, the process of recognizing people using them is far more difficult than using footprints.

The goal of this project is to turn 'Al-Qeiyafah' procedure into an intelligent system. Using image processing techniques, the system extracts foot trace features from an input image. Advanced deep learning approaches are used in the tracing identification system to help discover traces and recognize the attributes of each trace quickly. We employ the convolution neural networks approach in the suggested system to estimate the foot trace owner based on attributes derived from the performed system.

For this objective, we proposed our system, Where We will train a convolutional neural network that predicts age and gender from an image containing a person's footprint by using a CNN model for extracting the image's features. the model is composed of two parts, a pre-trained model and a classifier. The pre-trained VGG16 model was nominated for integration into the system classifier (Softmax).

The obtained results show clearly their accuracy, As the program was working efficiently, we eventually obtained satisfactory results, where the accuracy was 96.5%, but it is still insufficient to solve the aspect of human Barefoot traces recognition. In addition, some aspects could be improved.

Keywords: Image processing, Convolutional Neural Network, Softmax layer, VGG16, Pre-trained model, Foot trace, Barefoot trace, binary Model classification, Multi-Model classification.

الملخص

في الماضي ، كان علم التتبع يُعرف بعلم "القيافة" ، وفيه يستنتج خبير بدوي معلومات حيوية عن شخص من آثار أقدامه. بالإضافة إلى ذلك ، يعد التعرف على الإنسان أحد أكثر المجالات شيوعاً في رؤية الكمبيوتر. يعد التعرف على القياسات الحيوية باستخدام الإصبع أو القزحية ، أو مسح بصمة القدم ، الطريقة الواعدة التي يتم البحث عنها حالياً لهذا الغرض. نظراً لأن آثار الأقدام تفتقر إلى الخصائص البيومترية ، فإن عملية التعرف على الأشخاص الذين يستخدمونها أصعب بكثير من استخدام آثار الأقدام.

الهدف من هذا المشروع هو تحويل إجراء "القيافة" إلى نظام ذكي. باستخدام تقنيات معالجة الصور ، يستخرج النظام ميزات تتبع القدم من صورة الإدخال. تُستخدم مناهج التعلم العميق المتقدمة في نظام تحديد التتبع للمساعدة في اكتشاف الآثار والتعرف على سمات كل أثر بسرعة. نحن نستخدم نهج الشبكات العصبية الالتفافية في النظام المقترح لتقدير مالك تتبع القدم بناءً على السمات المشتقة من النظام المنفذ.

لهذا الهدف ، اقترحنا نظامنا ، حيث سنقوم بتدريب شبكة عصبية تلافيفية تتنبأ بالعمر والجنس من صورة تحتوي على بصمة شخص باستخدام نموذج CNN لاستخراج ميزات الصورة. يتكون النموذج من جزأين ، نموذج مدرب مسبقاً ومصنف. تم ترشيح نموذج VGG16 المدرب مسبقاً للتكامل في مصنف النظام (Softmax) .

تظهر النتائج التي تم الحصول عليها بوضوح دقتها ، حيث كان البرنامج يعمل بكفاءة ، حصلنا في النهاية على نتائج مرضية ، حيث كانت الدقة ٥.٦٩٪، لكنها لا تزال غير كافية لحل جانب التعرف على آثار حافي القدمين. بالإضافة إلى ذلك ، يمكن تحسين بعض الجوانب.

كلمات مفتاحية: معالجة الصور ، الشبكة العصبية التلافيفية ، طبقة Softmax ، VGG16 ، نموذج مدرب مسبقاً ، تتبع القدم ، تتبع حافي القدمين ، تصنيف نموذج ثنائي ، تصنيف متعدد النماذج.

Table of contents

List of Figures

List of Tables

Acronymes

HBFT: Human BareFoot Trace.
HBFTs: Human BareFoot Trace system.
MMC: Multi Model classification.
BMC: Binary Model classification .
MV: Machine Vision.
CV: Computer Vision.
IP: Image Processing.
IR: Image Recognition.
AI: Artificial Intelligence.
ML: Machine Learning.
DL: Deep Learning.
NN: Neural Network.
CNN: Convolusion Neural Network .
KNN: K-Nearest Neighbor.
SVM: Support Vector Machines.

Introduction

The identification of the barefoot print is one of the ancient habits of the Bedouins to access important information that allows the identification of the owner of the footprint.

Foot trace recognition study is one of the newly emerging sciences which has many challenges in various aspects, such as the unavailability of the dataset is one of the biggest barriers to the success of this study. The lack of scientific competencies and material capabilities that specialize in collecting accurately the traces. The climate change factors lead to hiding or erasing the traces.

In the criminal science field, many technical investigators are working on developing intelligent systems to recognize and identify the traces of the crime scene. for saving the lives of many beings, especially humans. such as the loss of people in the desert, which makes the search in this area very difficult. Depending on this phenomenon, fast technical solutions must be found to help find the missing people in the shortest time.

This work is about The identification of the barefoot print based on developing an intelligent system that uses advanced computer vision techniques to identify the barefoot footprint and predict the age group to which it belongs. The image data of foot trace can be collected by various means such as Drone, satellite planes,...etc. Considered these devices as image sources.
We will train a convolutional neural network that predicts age and gender from an image containing a person's footprint by using a CNN model for extracting the image's features. the model is composed of two parts, a pre-trained model and a classifier. The first part is a pre-trained model as a features extractor was chosen the VGG16 pre-trained model. While the second part presents our proposed classifier which is a softmax classifier.

This thesis includes four chapters. In the first chapter, we discussed the basic concepts of the human Barefoot trace. Also, the approaches and methods used to build the systems architectures. in this study, such as machine learning, deep learning, and Computer vision. Then, in the second chapter, we define the various forensic analysis techniques and approaches for the examination of bare footprint analysis and identification by considering marks left by the foot in its surrounding environment.

The third chapter is the main chapter because it defines our proposed system by explaining the general outline of the system, as well as a detailed explanation of each stage and step in the system, in the last chapter, we will discuss the results of implementing this proposed system.

Finally, we draw a broad conclusion about the acquired results and future research using the approaches employed.

Chapter 1

State of the art

Introduction

Artificial intelligence is used to improve the lives of humans through advances in computer technology, computer vision is used to reproduce human vision, and indeed the current development of computer vision is moving and aimed at more general learning areas such as recognition and detection.

A trace is a trial, sign, vestige, or evidence of the former existence that helps to know the truth of what happened before leaving the place of traces and who is its owner.

In this chapter, we will highlight the human Barefoot trace. So, we show the basic concepts of foot trace. Also, we present the approaches and methods used in this research.

1.1 basic concepts

In this section, we show the basic concepts of foot trace and the types of traces. Besides, the places categories where the traces can be found.

1.1.1 Foot

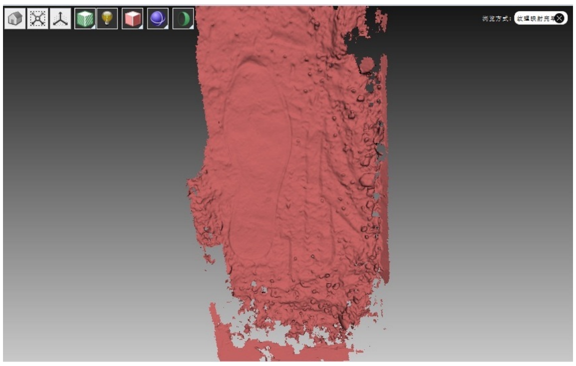
The foot is a complex and strong mechanical structure, it is the lowermost point of the human leg. As recognized by Defoe (1719), the human foot is also distinctive from the foot of non-humans and is unique because it is best suited to the style of bipedal locomotion. it makes humans capable of not only walking, but also running, climbing, and countless other activities [27, 40].

1.1.2 Trace

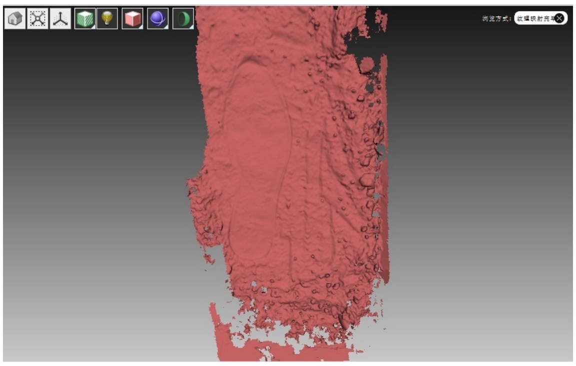
trace is a surviving mark, or evidence of the former existence, influence, or action of some agent or event vestige it's a barely discernible indication or evidence of some quantity, quality, characteristic, expression...
Traces can be classified into three types it is Trace of humans, Trace of Animals and Trace of Things. it is founded in different places that differ according to their nature, location, and climate. The latter is classified according to its characteristics into three categories it is Sand, Floor and Snow [27].

1.2 Foot trace recognition

Foot trace recognition is the ability to track the foot trace, It is called the science of Al-Qiyafah (the science of tracking the foot trace) in the Arabs. The first appearance of this science with the human in primitive life hunting. It was also mentioned In the Holy Quran in Surah Al-Kahf [27]. The science of Al-Qiyafah is a traditional human knowledge of tracing in the Arabian desert. It helps to distinguish between a woman's foot and a man's foot, the young man's feet and the young woman's feet and determining their height and weight, and more Until it became an accredited profession used to detect criminals, thieves, deserters, and missing persons. Most of the trackers are nomads and desert dwellers. Many modern security services still rely on an expert person who can identify and track a footprint [27]. Previously, to obtain a three-dimensional model of the track, they had to take measurements manually. Now, forensic experts use the Artec MHT scanner as shown in the figure 1.1 [13].
As technology develops, Both scans are imported into special software which was developed jointly by Beijing University of Technology-CAUP, the city police of Zhoukou, and Beijing Coase Instrument Company Limited. The program allocates different colors to different depths of the footprint topography (the closer the color is to red, the higher the topographic point – the closer to blue, the deeper) as can be seen in the figure 1.2 [13].
this specials software is not yet available as it is still being tested [13].



(a) Scan footprint at the crime scene



(b) Scan footprint of suspect

Figure 1.1: Example of scan footprints at crime scenes and suspect. a) Scan footprint at the crime scene. b) Scan footprint of suspect [13].

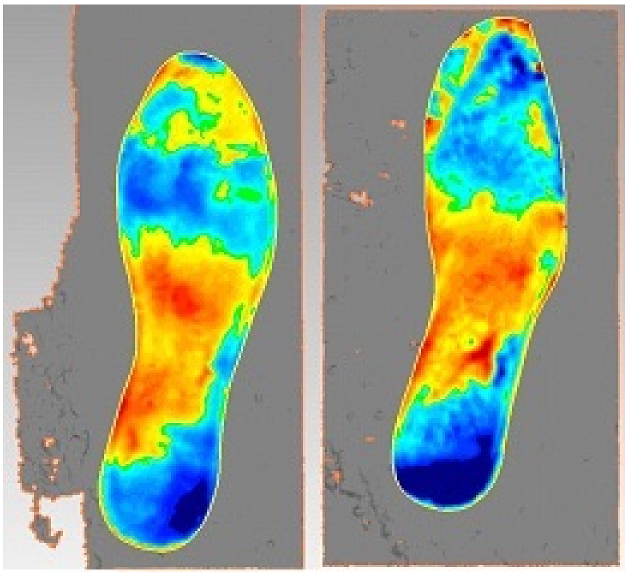


Figure 1.2: topography scans analyzes [13].

1.3 Technical disciplines

In this part, we want to highlight Technical methods, which are machine vision, computer vision, image recognition, and image processing, and we present the global architecture of a computer vision system.

1.3.1 Machine vision

Machine vision is the ability of a computer to see. First of all, it employs one or more video cameras, analog-to-digital conversion (ADC) and digital signal processing (DSP) to create a sequence of images. After that, the resulting data goes to a computer or robot controller for processing. The latter includes the use of machine vision which is similar in complexity to voice recognition. there are two important specifications in any vision system, sensitivity and resolution.Machine vision includes methods for acquiring, processing, analyzing, and understanding images and, in general, high-dimensional data from the real world to produce numerical or symbolic information, e.g., in the form of decisions [27, 5].

Figure 1.3 represents the important elements of a machine vision system.

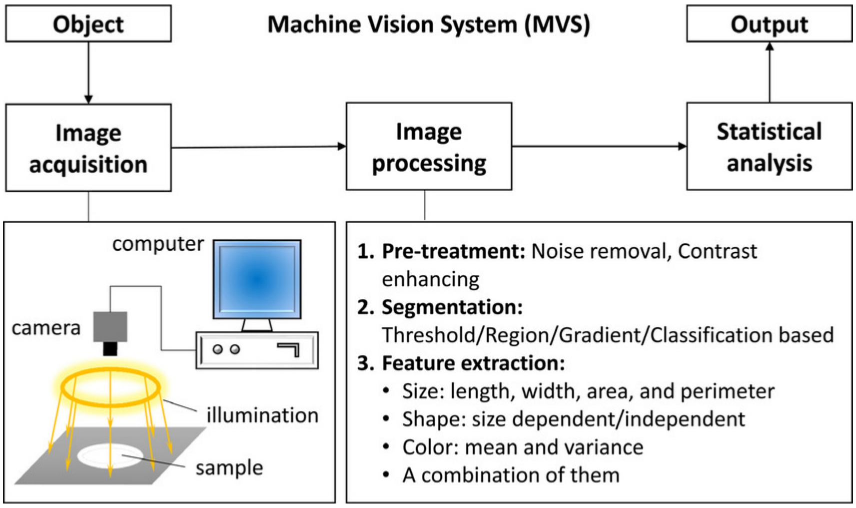


Figure 1.3: Architecture Machine vision [15].

1.3.2 Computer Vision

Computer vision is one of the most exciting fields of artificial intelligence (AI) that enables computers and systems to derive meaningful information from digital images, videos and other visual inputs and take actions or make recommendations based on that information. If AI enables computers to think, computer vision enables them to see, observe and understand [38]. The goal of computer vision is not only to observe data but also to process and provide useful results based on observation.

1.3.2.1 Computer vision technique

Image processing: is a method to perform some operations on an image, to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be an image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms a core research area within engineering and computer science disciplines too. There are two types of methods used for image processing namely, analog and digital image processing [11]. Image processing includes the following three steps [11] :

- Importing the image via image acquisition tools.

- Analysing and manipulating the image.
- Output in which result can be altered image or report that is based on image analysis.

1.3.2.2 Computer vision system

the computer vision system is highly application-dependent, the specific implementation of a computer vision system also depends on if its functionality is pre-specified or if some part of it can be learned or modified during operation. There are typical functions that are found in many computer vision systems.

1.3.2.2.1 A. Image Acquisition :

A digital image is produced by one or several image sensors besides various types of light-sensitive cameras, including range sensors, tomography devices, radar, ultra-sonic cameras, etc. Depending on the type of sensor, the resulting image data is an ordinary 2D image, a 3D volume, or an image sequence. The image taken is an array of pixels.

1.3.2.2.2 B. Pre-processing :

Before a computer vision method can be applied to image data to extract some specific piece of information, it is usually necessary to process the data to assure that it satisfies certain assumptions implied by the method. Preprocessing is a common name for image operations at the lowest level of abstraction, The aim of it is to improve and enhance the image data.

1.3.2.2.3 C. Feature extraction :

Image features at various levels of complexity are extracted from the image data. it helps to define certain objects, this Image features extracted can be Lines, edges, and ridges. Localized interest points such as corners, blobs, or points. More complex features may be related to texture, shape, or motion.

1.3.2.2.4 D. Decision making :

Making the final decision required for the application. Through the features extracted from the previous step, predicting the class of image.

1.3.3 Image Recognition

Image recognition is a subcategory of Computer Vision and Artificial Intelligence, It consists of a set of techniques for detecting, analyzing, and interpreting images to favor decision-making. It works through a neural network trained via an annotated dataset [17].

1.4 technical approach

artificial intelligence is essentially when machines can do tasks that typically require human intelligence. It encompasses machine learning and deep learning where machines can learn by experience and acquire skills without human involvement
In the next part, we will mention machine learning, and deep learning, in addition, we define the standard metrics to evaluate classification and explain the most important differences between them.

1.4.1 Machine learning

Machine learning is a method of data analysis that automates analytical model building. It is a branch of artificial intelligence who enables computer systems to learn from previous experience, based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention [27, 2].
Machine learning algorithms are classified into four types:

- Supervised machine learning.
- Unsupervised machine learning.
- Semi-supervised machine learning.
- Reinforcement learning.

1.4.1.1 Supervised machine learning algorithms

Def 1: Supervised Machine Learning is an algorithm that learns from labeled training data to help you predict outcomes for unforeseen data. In Supervised learning, you train the machine using data that is well "labeled." It means some data is already tagged with correct answers. It can be compared to learning in the presence of a supervisor or a teacher [19].
Def 2: In supervised learning, we feed the algorithm's output into the system so that the machine knows the patterns before working on them. In other words, the algorithm gets trained on input data that has been labeled for a particular output. The model undergoes training until it can detect the underlying patterns and relationships between the input data and the output labels, enabling it to yield accurate labeling results when presented with never-before-seen data[30].

The Figure 1.4 represents the supervised learning mechanism.

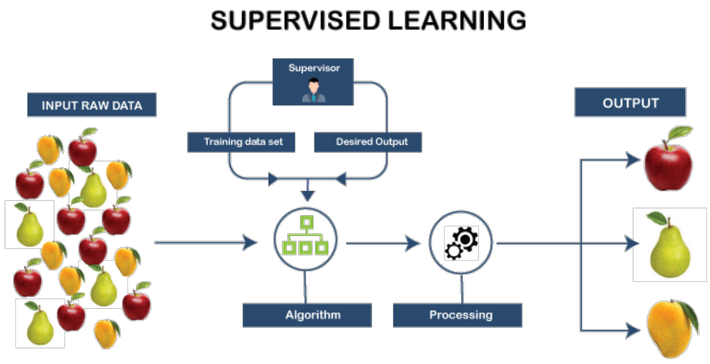


Figure 1.4: Architecture Supervised learning [30] .

Supervised learning can be further divided into two types of problems [18] :

1. *Regression*

Regression algorithms are used if there is a relationship between the input variable and the output variable. It is used for the prediction of continuous variables, such as Weather forecasting, Market Trends, etc.
Below are some popular Regression algorithms which come under supervised learning:

A. *Categorical:*

(Logistics, Neural Networks,. . .)

B. *Continuous:*

(Linear Regression ,Regression Trees, Non-Linear Regression,Bayesian Linear Regression , Polynomial Regression. . .)

2. *Classification*

Classification algorithms are used when the output variable is categorical, which means there are two classes such as Yes-No, Male-Female, True-false, etc.
Below are some popular Classification algorithms which come under supervised learning:

A. *Categorical:*

(KNN, Trees Naive Bayes, Support Vector Machines. . .)

B. *Continuous:*

(Random Forest, Decision Trees . . .)
We take Neural Networks, Support vector machines, and K-Nearest Neighbors as examples of supervised learning algorithms.

1.4.1.1.1 Neural Network

A neural network is an interconnected assembly of simple processing elements, units or nodes, which are a subset of machine learning techniques, whose functionality is loosely inspired by biological neural networks, the processing ability of the network is stored in the inter unit connection strengths, or weights, obtained by a process of adaptation to or learning from, a set of training patterns [27, 24]. As shown in figure 1.5

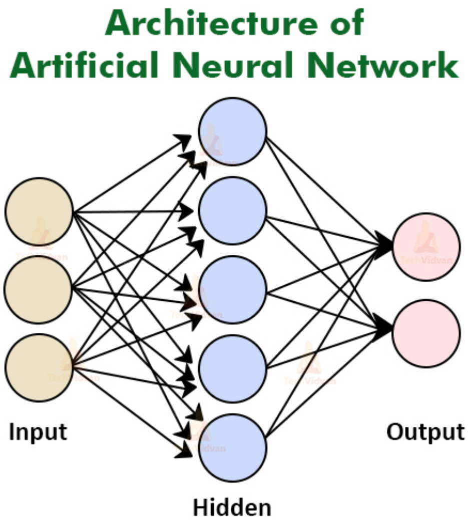


Figure 1.5: Architecture Neural Network [21] .

1.4.1.1.2 Support vector machines

Support Vector Machine(SVM) is a supervised machine learning algorithm that can be used for both classification and regression challenges. However, it is mostly used in classification problems.

In the SVM algorithm, we plot each data item as a point in n-dimensional space (where n is the number of features) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well.

Support Vectors are simply the coordinates of individual observation. The SVM classifier is a frontier that best segregates the two classes (hyper-plane/ line) [35].The architecture of the SVM is shown in figure 1.6

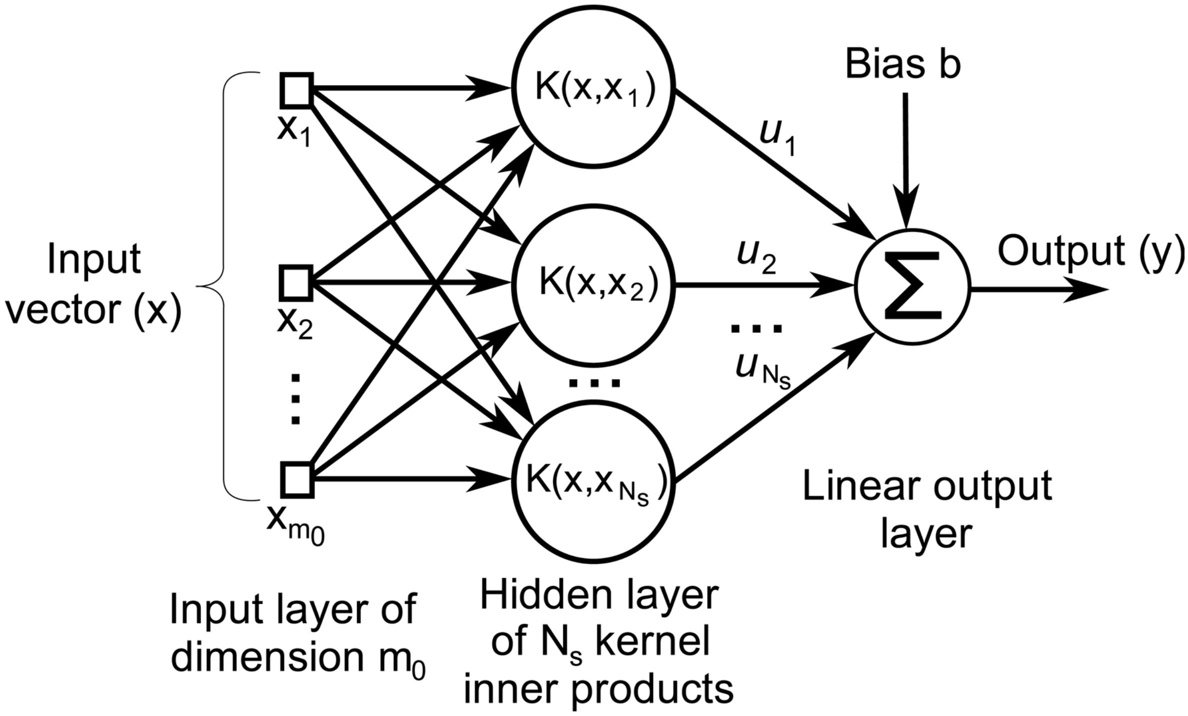


Figure 1.6: Architecture Support Vector Machine [35] .

1.4.1.1.3 K-Nearest Neighbors

K-nearest neighbors (KNN) is a type of supervised learning algorithm used for both regression and classification. KNN tries to predict the correct class for the test data by calculating the distance between the test data and all the training points. Then select the K number of points that are closest to the test data. The KNN algorithm calculates the probability of the test data belonging to the classes of 'K' training data and the class that holds the highest probability will be selected. In the case of regression, the value is the mean of the 'K' selected training points [22].

The architecture of the KNN is shown in figure 1.7

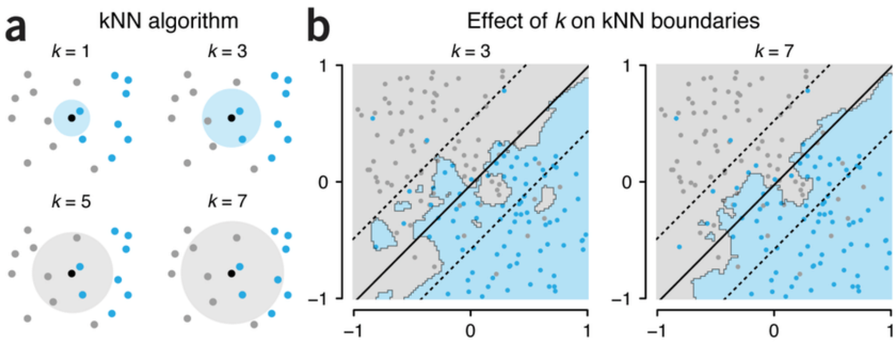


Figure 1.7: Architecture K-Nearest Neighbors [27].

1.4.1.2 Unsupervised machine learning algorithms

The unsupervised learning approach is fantastic for uncovering relationships and insights in unlabeled datasets. Models feed input data with unknown desirable outcomes. So, inferences are made based on circumstantial evidence without training or guidance. Machine Learning clustering examples fall Under This Learning algorithm [30]. as shown in figure 1.8

The important algorithms are:

A. Categorical:
association (Apriori, FP-Growth...), Hidden Markov Model...etc.

B. Continuous:
clustering (SVD, PCA, K-means...).

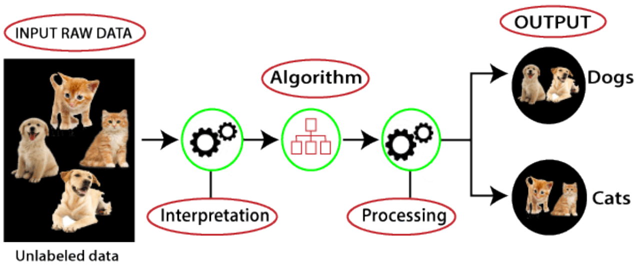


Figure 1.8: Architecture Unsupervised learning [30] .

1.4.1.3 Semi-supervised machine learning algorithms

Semi-supervised learning uses a combination of a small amount of labeled data and a large amount of unlabeled data to train models. Here the approach involves supervised machine learning using labeled training data, and unsupervised learning, which uses unlabeled training data [30]. The figure 1.9 shown the Semi supervised learning use case.

1.4.1.4 Reinforcement machine learning algorithms

The reinforcement learning approach in machine learning determines the best path or option to select in situations to maximize the reward. It follows the concept of the hit and trial method [27, 30]. The figure 1.10 shown the Reinforcement Learning Architecture

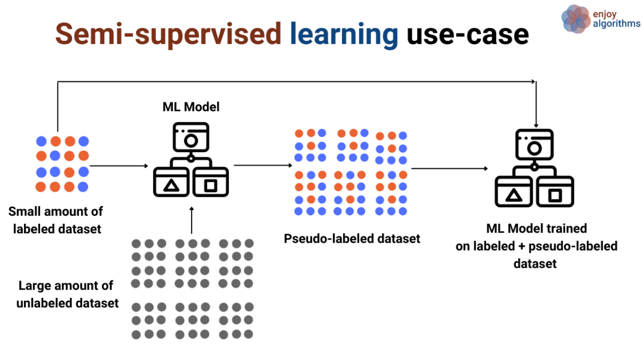


Figure 1.9: Architecture Semi supervised learning [30].

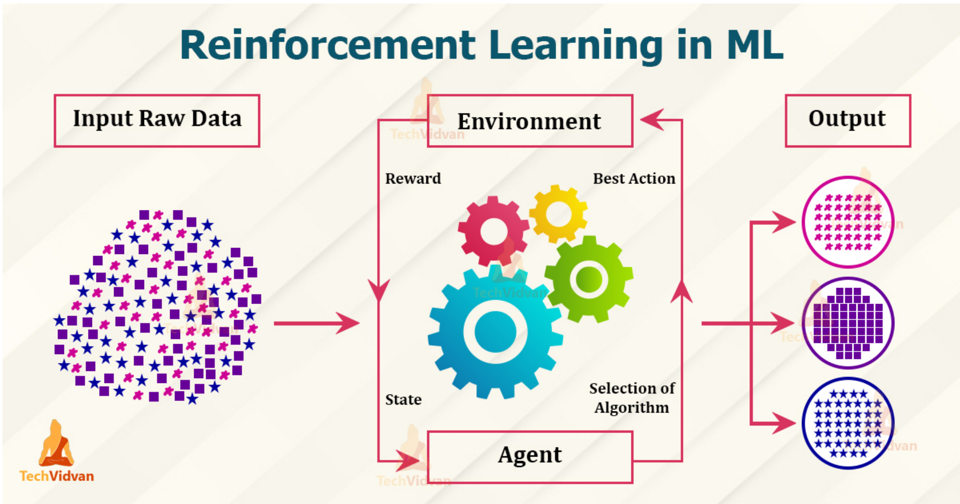


Figure 1.10: Architecture Reinforcement Learning [30].

1.4.2 Deep Learning

Deep Learning is a subfield of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks. Learn from large amounts of data. that makes it feasible [27, 1]. as shown in figure 1.11

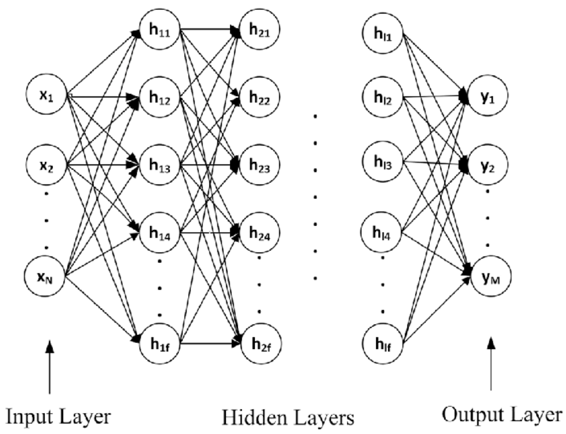


Figure 1.11: Typical deep neural network [36] .

deep learning has many Typical architectures are deep neural networks, convolutional neural networks(CNN), recurrent neural networks(RNN), generative adversarial networks(GAN), Long Short-Term Memory(LSTM), Deep Belief Networks (DBN), Deep Stacking Network(DSN)...etc

In this part, we mention convolutional neural networks, then we review the pre-trained models.

1.4.2.1 Convolutional Neural Networks

Convolution is a simple mathematical operation generally used for image processing and recognition, and it is one of the most used operations in deep learning for computer vision [27, 47] .

Convolutional Neural Networks, or CNNs in short, is a type of deep learning network that has become the popular choice of neural networks for different Computer Vision tasks such as image recognition, and image classification [27, 43].

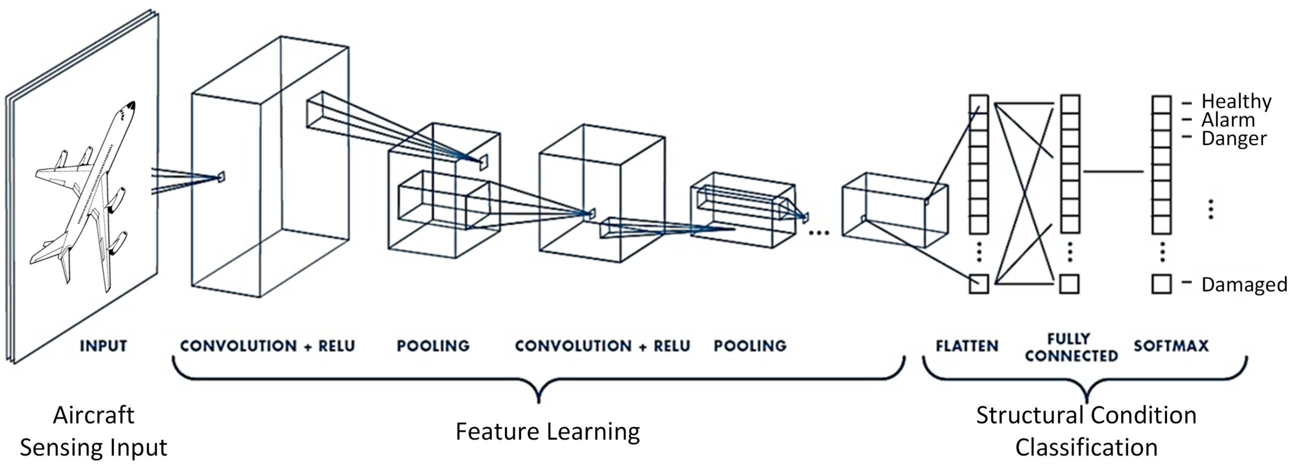


Figure 1.12: Example of a network with many convolutional layers [43].

Figure1.12 shown CNN layers perform operations that alter the data to learning features specific to the data. Three of the most common operations are convolution, and activation (ReLU), and pooling.

There are 4 primary steps or stages in designing a CNN[43] :

- ***Convolution:***The input signal is received at this stage
- ***Subsampling:***Inputs received from the convolution layer are smoothened to reduce the sensitivity of the filters to noise or any other variation

- ***Activation:***This layer controls how the signal flows from one layer to the other, similar to the neurons in our brain

- ***Fully connected:***In this stage, all the layers of the network are connected with every neuron from a preceding layer to the neurons from the subsequent layer.

1.4.2.2 Pre-trained models

a pre-trained model is a model created by someone else to solve a similar problem. Instead of building a model from scratch to solve a similar problem, you use the model trained on another problem as a starting point [32].
There are two uses of pre-trained models use the pre-trained model as-is for prediction or use transfer learning to customize this model to a given task [27].

1.4.2.2.1 Transfer Learning Transfer learning is a machine learning technique that enables data scientists to benefit from the knowledge gained from a previously used machine learning model for a similar task.
This technique applies to many machine learning models, including deep learning models like artificial neural networks and reinforcement models. The target is to leverage a pre-trained model's knowledge while performing a different task [48].
There are two ways to customize a pre-trained model:

1. Feature Extraction:
Feature extraction is a part of the dimensionality reduction process, in which, an initial set of the raw data is divided and reduced into more manageable groups [3].
Feature extraction helps to get the best feature from those big data sets by selecting and combining variables into features, thus, effectively reducing the amount of data. These features are easy to process, but still able to describe the actual data set with accuracy and originality [3].
The process of feature extraction is useful when you need to reduce the number of resources needed for processing without losing important or relevant information. Feature extraction can also reduce the amount of redundant data for a given analysis. Also, the reduction of the data and the machine's efforts in building variable combinations (features) facilitate the speed of learning and generalization steps in the machine learning process [25].

2. Fine-tuning CNN models:
Fine-tuning is a way of applying or utilizing transfer learning.

Specifically, Fine-tuning is a transfer learning technique that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem, relies on retaining the layers of the pre-trained CNN model which is responsible for feature extraction. In transfer learning, this first step is to place a set of new layers able to classify new classes [27, 45, 6].

1.4.2.2.2 Pre-trained models examples The following described are some of the pre-trained models:

- ***VGG 16 and VGG19:*** VGG is a classical convolutional neural network architecture and is one of the most popular pre-trained models for image classification. Introduced in the famous ILSVRC 2014 Conference(an annual competition called the ImageNet Large-Scale Visual Recognition Challenge), The network utilizes small 3 x 3 filters
  Otherwise, the network is characterized by its simplicity: the only other components are pooling layers and a fully connected layer, each with 4,096 nodes are then followed by a softmax classifier. The numbers "16" and "19" stand for the number of weight layers in the network [27, 39, 16].
  the Figure1.13 shown the VGG 16 model Architecture.

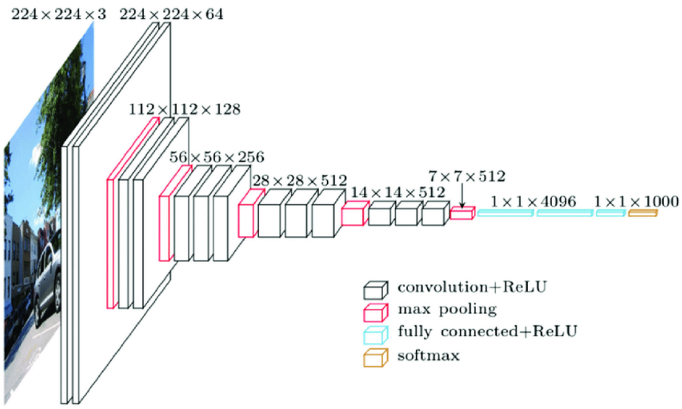


Figure 1.13: Architecture of the VGG 16 model [16] .

- ***ResNet 50:*** ResNet-50 is a deep residual network. First introduced in the Deep Residual Learning for Image Recognition paper. The "50" refers to the number of layers it has. It's a subclass of convolutional neural networks, with ResNet most popularly used for image classification. It uses blocks that reroute the input and add to the concept learned from the previous layer. During learning the next layer will learn the concepts of the previous layer plus the input of that previous layer [27, 46].

- ***Inception V3:*** Inception-v3 is a convolutional neural network architecture from the Inception family that was first introduced in the Going Deeper with Convolutions paper. that makes several improvements including using Label Smoothing and the use of an auxiliary classifier to propagate label information lower down the network (along with the use of batch normalization for layers in the sidehead). The goal of the inception module is to act as a multi-level feature extractor by computing 1×1, 3×3, and 5×5 convolutions within the same module of the network. The output of these filters is then stacked along the channel dimension, before being fed into the next layer in the network [27, 7].

- ***Xception:*** Xception is a deep convolutional neural network architecture that involves Depthwise Separable Convolutions. It was introduced in the CVPR paper, Xception: Deep Learning with Depthwise Separable Convolutions. It was developed by Google researchers.
  Google presented an interpretation of Inception modules in convolutional neural networks as being an intermediate step in-between regular convolution and the depthwise separable convolution operation (a depthwise convolution followed by a pointwise convolution). In this light, a depthwise separable convolution can be understood as an Inception module with a maximally large number of towers. This observation leads them to propose a novel deep convolutional neural network architecture inspired by Inception, where Inception modules have been replaced with depthwise separable convolutions. also, XCeption is an efficient architecture that relies on two main points, Depthwise Separable Convolution and Shortcuts between Convolution blocks as in ResNet [27, 14].

The following deep convolutional neural networks: VGG (VGG16 and VGG19),GoogLeNet (Inception V3 and Xception), and ResNet (ResNet50) architectures, shown in figure**??**, pre-trained for object detection task on the ImageNet dataset .

1.4.2.3 Model Evaluation Metrics

The most widely-used evaluation metric for image recognition models is the accuracy of test data because the accuracy can be calculated efficiently, which is an integral component of any data science project. It aims to estimate the generalization accuracy of a model on the future (unseen/out-of-sample) data.
they often correlate well with many standard metrics such as a confusion matrix, Accuracy, precision, F1-score, and recall [27, 4].

1.4.2.3.1 Confusion matrix A confusion matrix is a matrix representation of the prediction results of any binary testing that is often used to describe the performance of the classification model (or "classifier") on a set of test data for which the true values are known.
Each row of the matrix represents the instances in a predicted class, while each column represents the instances in an actual class (or vice versa) [27, 4].

1.4.2.3.2 Accuracy Accuracy is a common evaluation metric for classification problems. It's the number of correct predictions made as a ratio of all predictions made. accuracy can also be calculated by positives terms and negatives term, as follows:

$$Accuracy = \frac{TP+TN}{TotalPredictions}$$

Misclassification Rate(Error Rate): Overall, how often is it wrong. Since accuracy is the percent we correctly classified (success rate), it follows that our error rate (the percentage we got wrong) can be calculated as follows:

$$MisclassificationRate = \frac{FP+FN}{TotalPredictions}:$$

Where[27, 4] :
True Positive (TP): Predicted True and True in reality.
True Negative (TN): Predicted False and False in reality.
False Positive (FP): Predicted True and False in reality.
False Negative (FN): Predicted False and True in reality .

1.4.2.3.3 Precision Precision is the percentage of correctly classified as positive in the group that the classifier has declared positive. It is calculated by the next equation [27] :

$$precision = \frac{TP}{TP+FP}$$

1.4.2.3.4 Recall or Sensitivity Recall this is the percentage of observations labeled as positive that are correctly classified. It is calculated by the next equation [27] :

$$Recall = \frac{TP}{TP+PN}$$

1.4.2.3.5 F1-score The F1 score also called F 1-measure, is the harmonic mean of the precision and recall, where an F1 score reaches its best value at 1 (perfect precision and recall) and worst at 0. It is calculated by the next equation[27, 4] :

$$F1 - score = 2(\frac{(Precision)(Recall)}{Precision+Recall})$$

1.5 Comparison of deep learning and machine learning

In this part, we want to present the important key differences between machine learning and deep learning are:

Deep learning is a subset of machine learning. While both fall under the broad category of artificial intelligence. Machine learning uses algorithms to parse data, learn from that data, and make informed decisions based on what it has learned. While Deep learning structures algorithms in layers to create an "artificial neural network" that can learn and make intelligent decisions on its own [33].

Table1.1 Below Shows difference keys between Deep Learning vs Machine Learning [20] :

Table 1.1: key difference between Deep Learning vs Machine Learning [20] .

Parameter	Machine Learning	Deep Learning
Data Dependencies	Excellent performances on a small/medium dataset.	Excellent performance on a big dataset.
Hardware dependencies	Work on a low-end machine.	Requires powerful machine, preferably with GPU: DL performs a significant amount of matrix multiplication.
Feature engineering	Need to understand the features that represent the data.	No need to understand the best feature that represents the data.
Execution time	From a few minutes to hours.	Up to weeks. Neural Network needs to compute a significant number of weights.
Interpretability	Some algorithms are easy to interpret (logistic, decision tree), some are almost impossible (SVM, XGBoost).	Difficult to impossible.

Conclusion

A trace is a sign, vestige, or evidence of the former existence that helps to know the truth of traces and who is its owner. In this chapter, we discussed the basic concepts of the human Barefoot trace. Also, the approaches and methods used for dealing with such information such as machine learning, deep learning, and Computer vision, this last one is one of the most exciting fields of artificial intelligence (AI) that enable computers and systems to derive meaningful information and take actions or make recommendations based on that information.

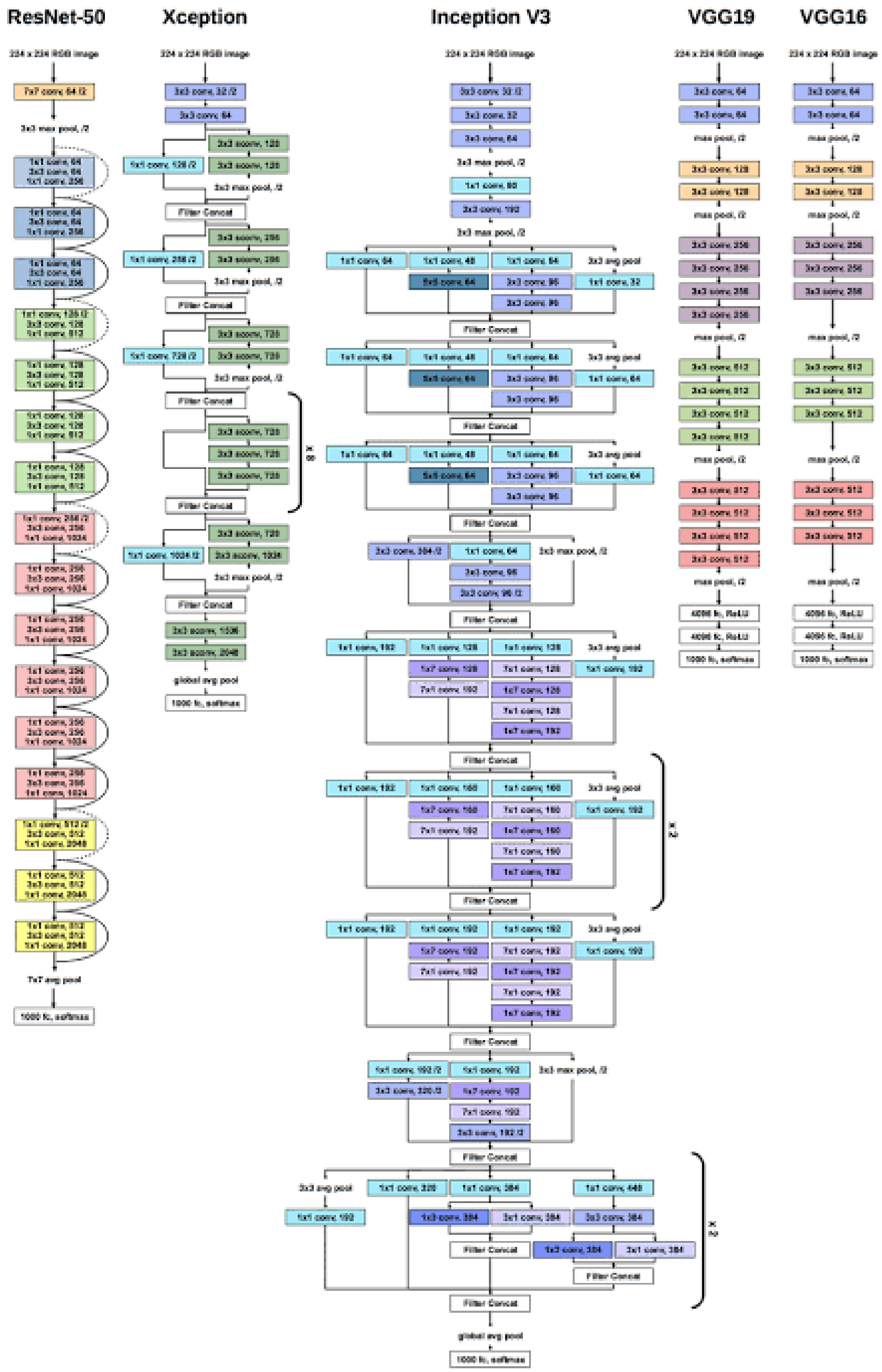


Figure 1.14: Architecture of VGG16, VGG19, Inception V3, Xception and ResNet50 [41] .

Chapter 2

Human Barefoot print identification

Introduction

The foot is an anatomical region that demonstrates a high degree of individuality, the human foot is also distinctive from the foot of non-humans. Also, it is possible to identify a person by considering the marks left by the foot it plays an important role in establishing the identity of a person, therefore, its examination is of prime importance. Unknown foot marks are compared directly with the footprints of a known individual and a conclusion is reached as to whether these marks shared common ownership. The evaluation and interpretation of footprints are not only of prime importance in the forensic examination but also help in clinical examinations and elucidation of various podiatric disorders. Fundamentally, the identification process uses plantar prints or impressions. Several techniques have been derived, but initially use various anatomical measurements (heel-to-toe measurements, the angles between these measurements, and across-foot distances) to describe footmarks. These measurements can then be compared with Other marks whose owner is known, to obtain a potential owner. Currently, there are four main sub-specialties within the scope of practice of forensic podiatrists:

1. Analysis and Identification involving Podiatry Treatment Records.
2. Barefoot prints.
3. Footwear.
4. Gait Patterns.

The three last elements are the only ones with relation to barefoot identification.

2.1 Barefoot prints and methods identification

Individual footprints are unique as fingerprints and can be used for human identification purposes. Even monozygotic twins have different footprints; Many researchers have been using different techniques for evaluation of bare footprints; whether they are inked prints or prints obtained by the Podotrack (A Podotrack is a simple footprint mat for measuring plantar pressure), or 3-dimensional casts made of dental plaster or clay. All such techniques of footprint analysis have different approaches for the assessment of linear as well as angular measurements. A perfect footprint must include 5 toes, a ball of foot impression, heel impression, lateral mid-foot impression and arch profile. With all of these features, the size, the orientation and the shape help the identification [27, 9].
Several techniques have been employed for barefoot identification, which includes:

1. The Gunn method; The Extended Gunn Method.
2. The Optical Center Approach.
3. The Overlay method.
4. The Robbins method.
5. The Rossi's podometric system.
6. The Reel Method.

2.1.1 The Gunn Method

This method is developed in 1970, by the Canadian forensic podiatrist Dr. Norman Gunn and was used in the assessment, comparison and evaluation of planter prints. The basic idea is to draw six lines; five lines from the bottommost side of the heel print to the tip of each toe print and one line is drawn across the widest part of the ball of the foot.(see figure2.1) The Gunn method is applicable only if a complete form of the footprint is found and evaluated[27, 8].

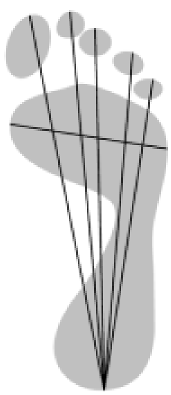


Figure 2.1: The Gunn Method[27].

These lines are measured and compared between two separate footprints, In addition, to enforce comparisons angles between lines from point to point are used as points of comparison. The basic measurements and angles used in the Gunn Method are :

1. Heel to first toe;
2. Heel to second toe;
3. Heel to third toe;
4. Heel to fourth toe;
5. Heel to fifth toe;
6. Heel to first toe line — intersection with cross ball line;
7. Heel to second toe line — intersection with cross ball line;
8. Heel to third toe line — intersection with cross ball line;
9. Heel to fourth toe line — intersection with cross ball line;
10. Heel to fifth toe line — intersection with cross ball line;
11. Angle between heel to first toe and heel to second toe lines;
12. Angle between heel to first toe and heel to third toe lines;
13. Angle between heel to first toe and heel to fourth toe lines;
14. Angle between heel to first toe and heel to fifth toe lines.

2.1.1.1 The Extended Gunn Method

if there is a recovery of any partial footprint where the heel part of the footprint is missing or smudged due to any circumstances, then the technique used for analyzing the whole footprint will not be applicable. Therefore, an extended version of the same was established which involved the examination of the partial footprint. In this, the same series of six lines are sketched from any of the points acting as a reference to measure the lengths and the width of the foot, the method of comparison is the same as that in the case of the previously described system (see figure2.2) [8].

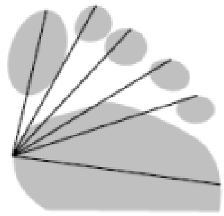


Figure 2.2: The Extended Gunn Method [27].

2.1.2 The Optical Center Approach

It is the development of Gunn. In which, a circle was drawn to the heel area and each toe that best fit it and lines were drawn from the circle's center of each toe to the circle's center of the heel. it was developed by the Royal Canadian Mounted Police to demonstrate the individuality of the human footprint. The latter consists of determining the central point of a morphological feature as defined by the center of a circle when placed in a position of best fit.(see figure2.3) In this huge study, a computer database has been produced of 24,000 human footprints, to evaluate and compare the footprint. It was Kennedy who in 2003 further revised this method and used optical centers instead of lines joining the apex of the toes and heel. Kennedy scanned the footprints into the AutoCAD software where these optical centers are imposed digitally. Several lines are created from these optical center points of the toe to the center points of the heel. Also, another line is added across the widest area of the ball of the foot area. Finally, a set of measurements from different lines (from point to point) and angles are taken to compare different footprints. This approach permits obtaining a total of 38 variable measurements [27, 8, 9].

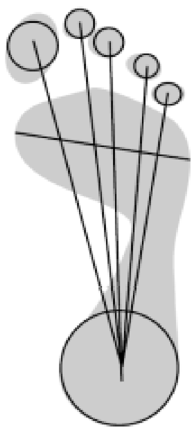


Figure 2.3: The Optical Center Approach[27].

2.1.3 The Overlay Method

This method is developed and used by forensic science services In 2005, in the U.K. the forensic experts put a transparent sheet of paper over the recovered prints. In this method, an outline of the print is marked carefully with a sharp end pen to produce the least possible error. The outlined morphology of the print so obtained on the sheet is then transferred onto the exemplar prints for finding out further similarities and differences. Such a method can be used for comparing any kind of print (either complete or partial). No linear or angular measurements are used in this method instead it depends upon the marking of the outline around the print. Along with the shape and size of the print, a lot more detailing of the barefoot can be observed like the shape of the toe, presence or absence of any part of the foot, any injury or scar details in the print, etc[27, 8, 9].

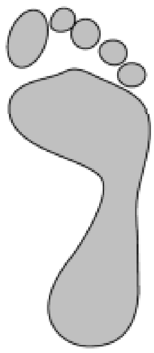


Figure 2.4: The Overlay Method[27].

2.1.4 The Robbins Method

It is a quantifiable method; this method was designed by forensic anthropologist Louise Robbins in 1985 for evaluating footprints by using parallel as well as diagonal lines to determine lengths at different parts of the footprint. Those lines are drawn from a theoretical baseline across the rear of the heel to the tips of each toe. Also, a declination angle is drawn between the tips of the first toe to the fifth toe.(see figure2.5)[27, 8, 9].

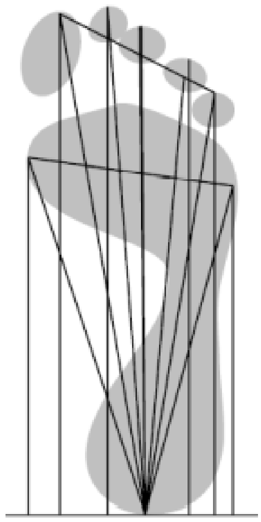


Figure 2.5: The Robbins Method [27].

According to Robbins, the method includes the assessment of both two-dimensional as well as three-dimensional footprints leading to several measurements including lengths, widths, and angles. She followed different rules for examining the prints. Apart from this, several other measurements were taken on the footprints[8]:

- ***Length Measurements:***

  1. Toe-Pad Length (length of the toe pad print).
  2. Toe-Stem Length (length of the toe stem).
  3. Heel to Ball Length (also known as Instep length is the distance between the ball and the heel).
  4. Heel to Arch Length (from the arch region landmark to the Base line and to the pternion).
  5. Heel length.

- ***Width Measurements:***

  1. Toe width (distance between the most medial and lateral sides of the toe) .
  2. Ball width This is further divided into two parts, i.e. horizontal width and the other as diagonal width of the ball region. Both the measurements are calculated from the medial metatarsal points of the ball.
  3. Heel width This is further divided into two parts, i.e. horizontal width and the other as diagonal width of the ball region. Both the measurements are calculated from the lateral calcaneal bony tubercle of the heel.

2.1.5 The Rossi's Podometric System

the American podiatrist William Rossi, 1992 invented a method of categorizing landmarks of the foot. whose focus was to obtain the rearmost side of the heel while measuring the footprint to maintain the reliability of the method [27, 8, 9]. The method was based on drawing triangular lines longitudinally and transversely across the footprint. The procedure involves drawing Two tangents, one from the medial side of the heel to the medial side of the ball and the other from the lateral side of the heel to the lateral side of the ball of the foot; and intersect when traced backwardly gives secondary measurements. After that, three other-centered lines are added in between the existing lines. Similarly, the other five lines are added laterally.(see figure2.6)[27, 8, 9].

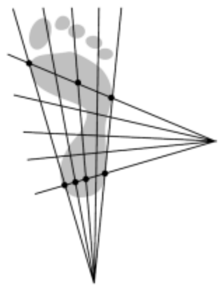


Figure 2.6: The Rossi's Podometric System [27].

2.1.6 The Reel Method

This method is developed by Sarah Mai-Lin Reel in 2012 The basic idea In this system is that an Inkless Shoeprint Kit' is used to achieve two-dimensional static as well as dynamic prints of the foot. The print so obtained is scanned and made digitized using an Epson scanner and is further transferred to 'Freeware GNU Image Manipulation Program (GIMP) Version 2.2.17' for evaluation. Using prior literature various length, width and angular measurements are taken on the scanned prints. A central axis is drawn by bisecting the inner and outer tangents from the medial and lateral margin of the footprint. A grid is superimposed on the print using the software and the central axis of the foot is aligned with the vertical axis of the grid. Once the print is aligned, a horizontal line is marked at the posterior point of the foot and its intersection with the central axis acts as a reference point for other measurements (see figure2.7)[8, 9].
The length, width and angular measurements that are extracted from the scanned print proposed by Reel are as follows [8] :

- ***Linear measurements:***
    1. CalcA1 (Length line from base of heel print to apex of first toe)
    2. CalcA2 (Length line from base of heel print to apex of second toe)

3. CalcA3 (Length line from base of heel print to apex of third toe)
4. CalcA4 (Length line from base of heel print to apex of fourth toe)
5. CalcA5 (Length line from base of heel print to apex of fifth toe)
6. Metatarsophalangeal joint (MPJ) Width (Widest section of the forefoot print)
7. Calcaneum Width (measurement across the widest part of the heel print)

- ***Angular Measurements:***

1. Footprint angle (angle between the inner tangent, most medial point of the metatarsal area and the apex of concavity of the arch of the footprint)
2. Distal metatarsal angle (angle of declination of the metatarsal ridge that separates the ball of foot from the toe prints)
3. 2-4 base angle (angle of declination from the base of the second toe print to the base of fourth toe print)
4. 2-5 toe angle (angle of declination from the apex of the second toe print to the apex of fourth toe print)
5. 1-5 toe angle (angle of toe declination from the apex of the first toe print to the apex of the fifth toe print).

2.2 Comparison between barefoot print methods :

The six methods mentioned were used in different circumstances to identify human barefoot prints. Table2.1 shows the different aspects of each of them [27, 9].

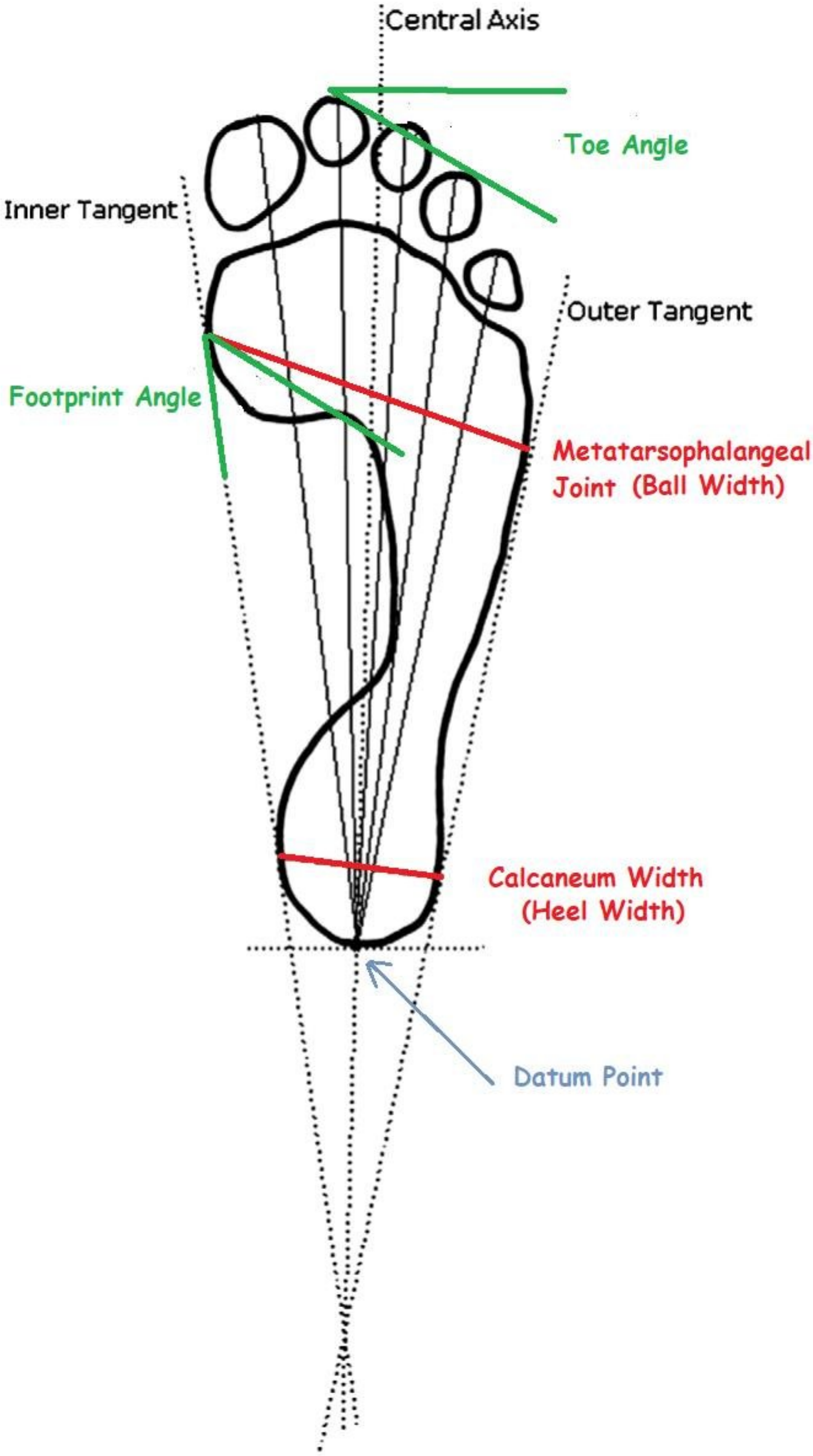


Figure 2.7: The Reel Method Measurements [42] .

Table 2.1: Comparison between barefoot print methods [27, 9].

	Gunn Method	Optical Center Approach	Overlay Method	Robbins Method	Rossi's Podometric System	Reel Method
User friendly	Yes	Yes	Yes	No	No	Yes
useful for partial footprint	Yes	No	No	Yes	No	No
Allows quantitative measurement	Yes	Yes	Yes	No	Yes	Yes
allows detail comparison	Yes	No	No	Yes	No	No
Devised for identification	Yes	No	No	Yes	Yes	Yes
Examine whole footprint	Yes	Yes	Yes	No	Yes	Yes
Repeatability validated	Yes	No	No	No	Yes	No

Conclusion

The footprints are important from both clinical as well as from forensic perspectives. Forensic podiatrists are professionals specializing in feet that have expertise levels related to the foot. In this chapter, we discussed the various forensic analysis techniques and approaches for the examination of bare footprint analysis and identification, among these technologies that are used for the footprint analysis the Gunn's method, the Overlay method, the Robbins' method etc.; the Reel's method is found to be the most widely used technique for the evaluation and comparison of the footprint evidence.

Chapter 3

Design and Implementation

Introduction

Previously, we presented an overview of foot trace recognition, the basic concepts of the human Barefoot trace, and the methods to build the system architecture. Also, the various forensic analysis techniques for the examination of bare footprint analysis and identification. In this chapter, we will present the general outline of the human Barefoot trace system (HBFTs), as well as a detailed explanation of each stage and step in the system.

In this section, we explain the important general steps in the HBFTs design process which involves eight steps, as follows:

images or data acquisition, preprocessing, dataset construction, dataset preparation, feature extraction, classification, matching, and making decisions (as shown in figure3.1). We categorize these eight steps into two main stages, dataset generation and the system model construction. In the first phase, we generate and prepare data sets from primitive data to train our proposed model. For the second phase, we build the models through training and testing steps.

3.1 Dataset generation

In this phase, we collect and process a set of raw data to be clear and clean. We create a dataset for our proposed model based on the processed data. We conclude this stage by preparing the generated datasets for the models.

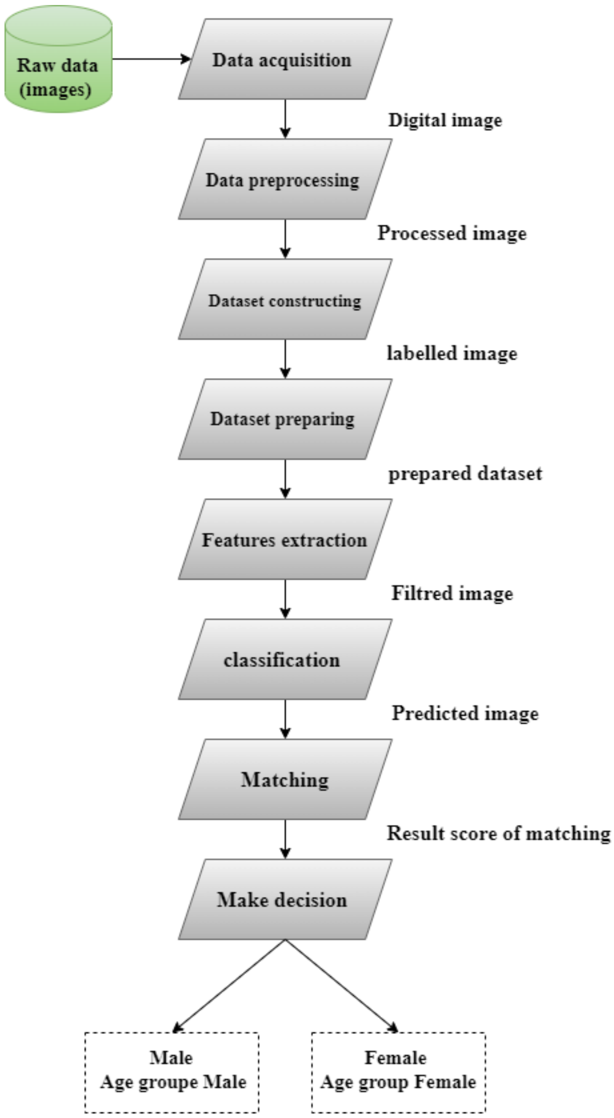


Figure 3.1: general steps of HBFTs design process.

3.1.1 Data acquisition

Due to unavailability of an existing dataset, we collected a set of human Barefoot trace images personally from 50 individuals (volunteers), at Djamaa, El-Oued. Each person has the most necessary information: ID, full name, tall, weight, and age(as shown in the figure 3.2). The total size of the collected data is 5.36 GB. The figure 3.3 shows some samples of the collected raw data (without processing).

Id	name	Tall	Wheight	Age	Gender	Age-grou
1	khaoula hadjaidji	1.50	55	12	Female	Child
2	rahma fraje	1.12	24	5	Female	Child
3	sabrin fraje	1.37	50	10	Female	Child
4	samira zinat	1.58	44	22	Female	Adult
5	hiba hadjaidji	1.05	22	4	Female	Child
6	farida	1.60	55	29	Female	Adult
7	aya kaddar	1.64	74	22	Female	Adult
8	kawther hadjaidji	1.65	50	23	Female	Adult
9	chaima ben salah	1.57	48	22	Female	Adult
10	Dounia Taabli	1.50	37	22	Female	Adult
11	abd nour fraje	1.70	60	15	Male	Teen
12	hamida barkate	1.55	51	63	Female	Senior-Adult
13	nizar	1.40	50	9	Male	Child
14	ilyass karini	1.50	38	15	Male	Teen
15	haydare ben dabka	1.05	20	4	Male	Child
16	farid	1.80	62	29	Male	Adult
17	boubaker hadjaidji	1.70	61	70	Male	Senior-Adult
18	abd ellah ben dabka	1.10	22	6	Male	Child
19	souad hadjaidji	1.60	55	32	Female	Adult
20	imad Taabli	1.68	70	22	Male	Adult
21	bachayer	1.05	22	4	Female	Child
22	abd errahman hadjaidji	1.68	60	29	Male	Adult
23	Mohamed ben	1.70	60	26	Male	Adult
24	hadjer Taabli	1.60	75	35	Female	Adult
25	badra sakhri	1.71	68	23	Female	adult
26	yasmine hadjaidji	1.39	48	10	Female	Child

Figure 3.2: Samples of volunteers information.

Figure 3.3: Samples of collected raw data.

For each one, we focus on taking images with some different situations which are: two feet together, a right foot, a left foot, and a set of footsteps. These images are taken by four devices, one redmi phone, OnePlus phone and Canon digital imaging device:

- camera Canon EOS 1200D :(18.0 MP DSLR with APS-C (22.3 x 14.9 mm) CMOS sensor).

- OnePlus Nord N100 :(triple photo sensor:13 megapixels (main),2 of two megapixels).

- Xiaomi Redmi 9A :(With a 13-megapixel camera and a 5-megapixel front camera).

3.1.2 Data preprocessing

The preprocessing step is necessary because it improves image quality. as images contain noise inherently, which can lead to reduced classification accuracy. It goes through three steps of preprocessing: selecting, cleaning, and enhancement.

3.1.2.1 Data selection

In this step, After the data was collected, we selected from it a set of images that showed the foot traces more clearly, and we excluded the rest of the data images . All data images were selected carefully and separately. The figure 3.4 shows a sample of the selected images (a) and excluded images (b).

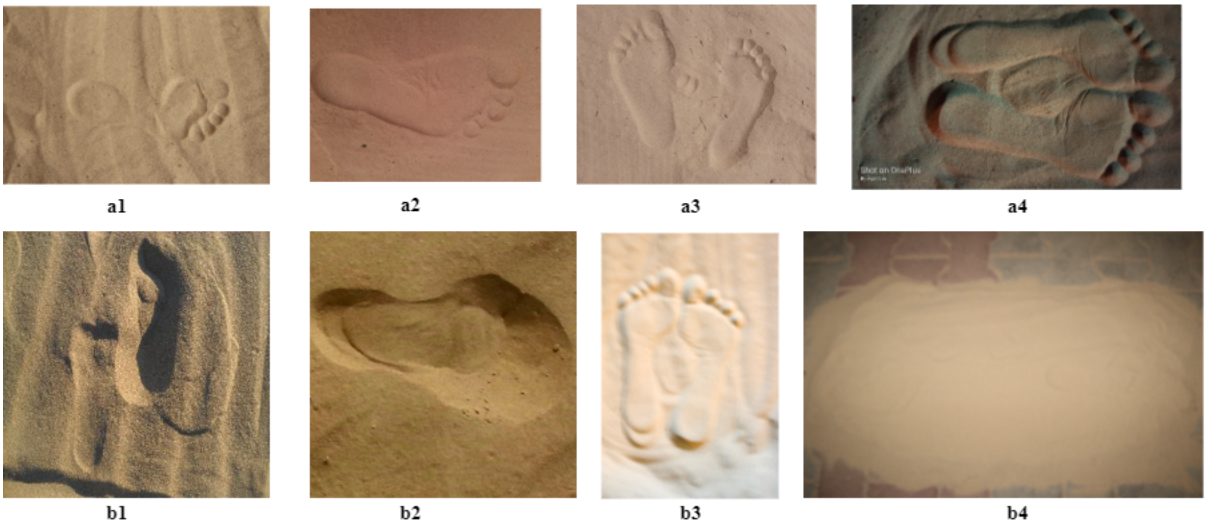


Figure 3.4: Samples of images: (a) selected images, (b) excluded images.

3.1.2.2 Data cleaning

We have done the process of cleaning manually to ensure that the images had no misleading traces of impurities. So, we cut some parts of the images because it includes many traces outside the foot traces of volunteers. Figure 3.5 shows some samples of the images including misleading traces of impurities.

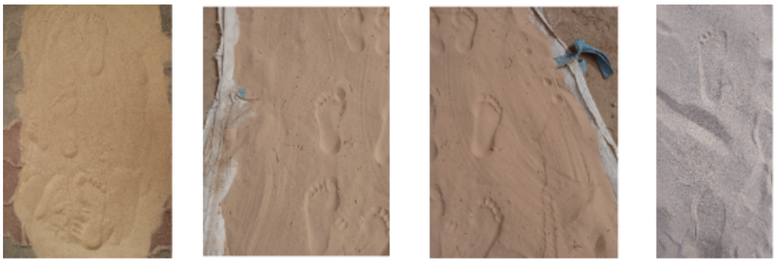


Figure 3.5: Samples of the images including misleading traces of impurities.

We filtered any impurities that might affect the quality and features of the image, to facilitate the automatic treatment later. Figure 3.6 shows some samples of foot traces images after being selected and cleaned.

Figure 3.6: Samples of foot traces images after selection and cleaning.

3.1.2.3 Data enhancing

After we select and clean the data images, we try several ways to improve the quality of each image. Therefore, we analyzed the images using histograms of pixel intensity values to study the possibility of applying filters of enhancements to these images.

We analyze the histogram of pixel intensity values of a given image (RGB color), depending on the conditions in which the image was taken and image type to choose the right filter of enhancement. We have done the process of cleaning manually to ensure that the images had no misleading traces of impurities. So, we cut some parts of the images because it includes many traces outside the foot traces of volunteers.

The images collected are in BGR format. Therefore, we need to convert them to an RGB format to get the RGB color histogram. The process uses a cvtColor function. The pixel intensity value is represented by three axes RGB, i.e. red, green, and blue channels. Figure 3.7 shows some histograms of two axes RGB for color images.

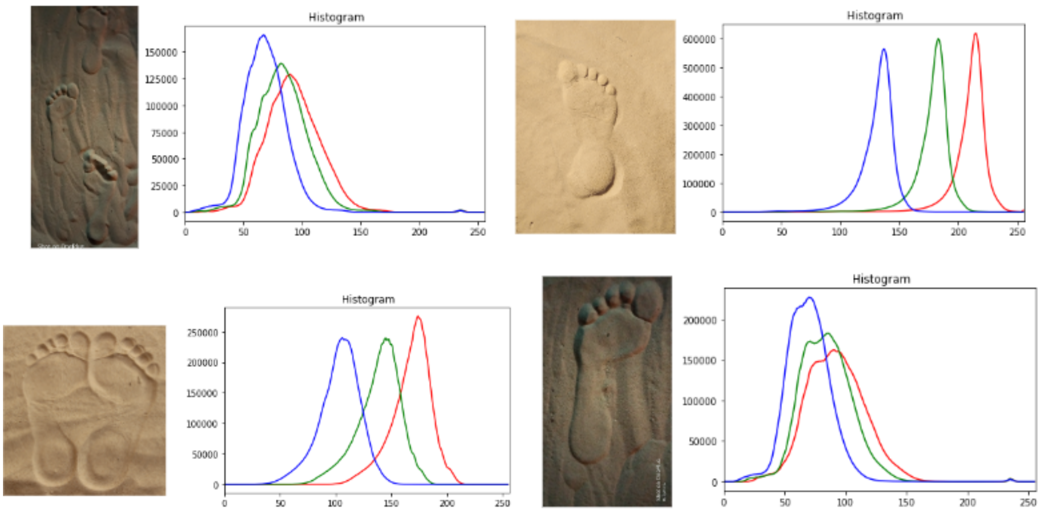


Figure 3.7: RGB color images of barefoot traces and its histograms.

3.1.3 Dataset constructing

In this step, we decided to use two constructions of a dataset in our proposed system. First, we analyze our processed data statistics for doing the primitive construction of the dataset.

In this case, the term construction means classifying data images (labeling) according to the requirements of the research. we propose two classifications of the data images according to our system:

- binary Model classification.
- Multi-Model classification.

3.1.3.1 Primitive construction

In this part, we present the processed data statistics, and their construction according to our proposed system, i.e. the construction of the first dataset for binary Model classification, and the construction of the second dataset for the Multi-Model classification.

After the preprocessing step, we get 50 individual (volunteers) data. For each individual, we create a folder named with the person ID, that contains his images and a text file of the necessary information. In addition, we add additional information (barefoot, gender, age group) to the Excel file that contains all the personal information related to the data images for each person.

The table 3.1 shows data statistics of different groups (sub-classes) of images.

Table 3.1: Data statistics of different groups (sub-classes) of images.

characteristic	***Type***	***Number of individuals***
Gender	Male	20 (40 %)
	female	30 (60 %)
Age Groupe	Kids	18 (36 %)
	Teenagers	11 (22 %)
	Youth	16 (32 %)
	elderly	3 (6 %)
	older	2 (4 %)

Through the table, we see 2 principal features, gender and age groups. After observing the features and evaluating them for 50 volunteers, we finish analyzing each feature in the following points:

- For the gender we have:
  - 40% of total participants who have barefoot images Male.
  - 60% of total participants who have barefoot images female.
- In the age groups feature, we have:
  - 36% of the total participants are Kids ([3, 12] years old).
  - 22% of the total participants are Teenagers ([13, 19] years old).
  - 32% of the total participants are Youth ([20, 39] years old).
  - 6% of the total participants are elderly [59, 40]) years old).
  - 4% of the total participants are older [60>=]) years old).

3.1.3.2 Dataset construction

The dataset is the important element in the process of building the model (i.e. the dataset used in the training and evaluates a model). In this step, we constructed the datasets from the primitive dataset, that contains representative samples of HBFT images. Ultimately, we summarize in a table the data set construction process.

3.1.3.2.1 Constructing binary Model classification dataset In this part, we create one dataset of 2 label, Male and female. Figure 3.8 shows dataset hierarchy to binary Model.

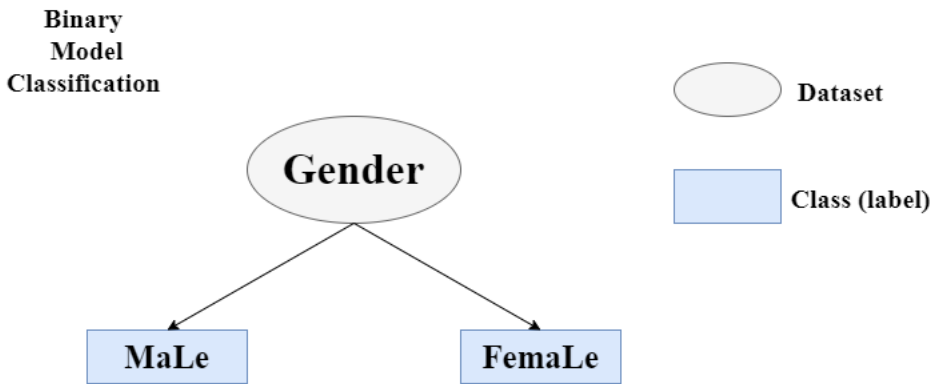


Figure 3.8: dataset hierarchy for binary Model.

3.1.3.2.2 Constructing Multi-Model classification dataset In this part, we create one dataset of 12 labels , Male/female. Kids, Teenagers, Youth, elderly, older of both sexes. The figure 3.9 shows the hierarchy of the data set of the multi-model.

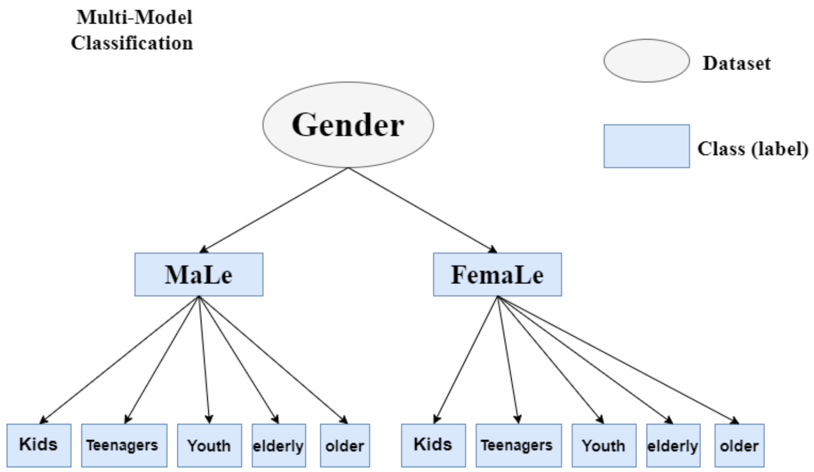


Figure 3.9: hierarchy of the data set for the multi-model .

After optimizing the previous structure by eliminating redundancy we have 2 subsets as shown in figure 3.10 .

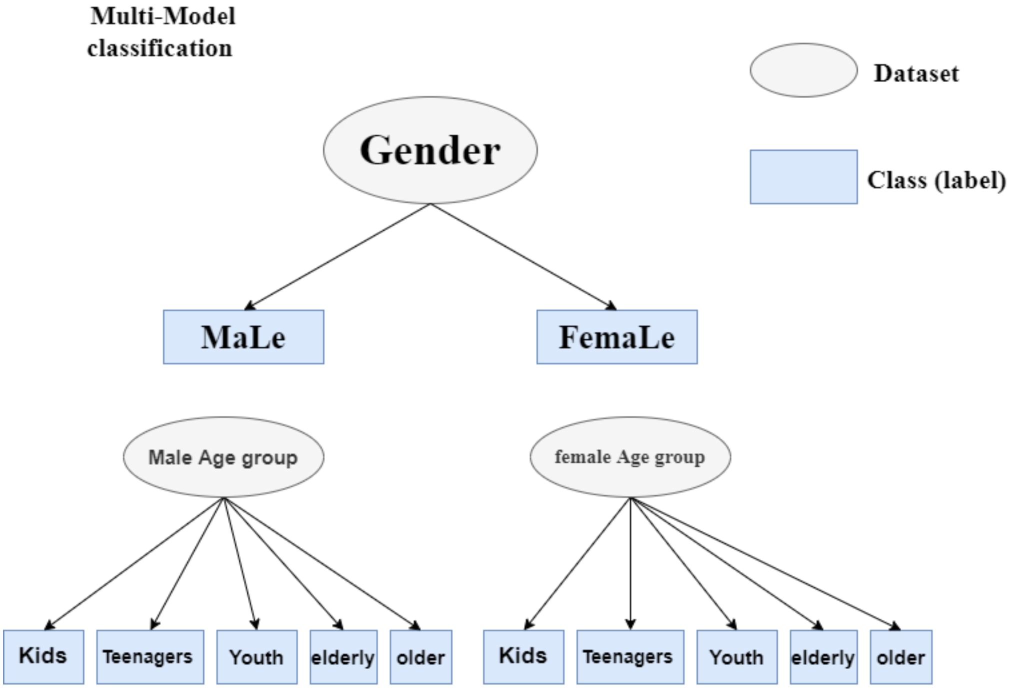


Figure 3.10: representation of the data set of the multi-modeloptimized.

Through the above figure, there are 2 different subsets, as follows:

Gender :

We split the primitive dataset into two subsets, the first one contains foot traces images of all person Barefoot Male. The second subset includes foot traces images of all person female Barefoot.

Age group dataset:

Based on the precedent dataset ' Gender ', we take each class ('Male 'and ' female ') to create two new datasets. The first one is the "Male Age group" dataset, and the second is the "female Age group" dataset.

Each subset, we split it into 5 classes, Kids, Teenagers, and Adults, elderly ,older.
So, we have now two new subsets, each one has 5 labels.

3.1.3.2.3 Dataset construction summarized The total dataset size is 1160 images for 50 individuals. Table 3.2 shows the subsets for each classification with the class size of each one.

Table 3.2: Dataset subsets and the class size for each classification.

System	ID	Datasets	Labels (classes)	Dataset size
Binary Model classification	1	Gender	2	1160
Multi Model classification	2	Gender	Male	393
			Female	767
	3	Male Age group	Kids	123
			Teenagers	112
			Adults	127
			elderly	32
			Older	15
	4	Female Age group	Kids	270
			Teenagers	93
			Adults	342
			elderly	22
			Older	22

3.1.4 Dataset preparing

Images in the dataset had different sizes and its label is not binarized, ...etc. Therefore, the images must be processed before being used by the model for training, feature extraction, classification,...etc. The same processing tasks are applied to all images to make them match the arguments of the target model.

The most important steps in the processing of a given input image are :

- Convert the image to an array.
- Swapping image color channels to RGB.
- Resizing images to a fixed size as an input tensor.
- Normalizing image.

3.1.4.1 Convert an image to an array

for making the model read each pixel of the image. we have to convert the image into a two-dimensional matrix. This matrix is a set of elements, each one is represented by three RGB color values. The values indicate the intensity of the red, green, and blue of the pixel. The value of each color is between 0 and 255.

3.1.4.2 Convert the image from BGR to RGB color format

To preserve the original color format of the image, we return the values to the RGB color format by inverting the three values for each pixel from the BGR color format to the RGB color format (i.e. from (blue, green, red) to (red, green, blue)). because When reading an image by some specific functions to convert it into an array, we get an array of values of the BGR color format. This auto-inversion of the color format from RGB to BGR while reading the image is due to some of the functions from specific libraries used for reading the image, such as CV2.imread(image) from library OpenCV in Python3.

3.1.4.3 Resize image

in this step, the input image is resized to be equal to the size of the model input layer. In our system we fixed our choice on the value 224x224 for all models.

3.1.4.4 Image normalization

In this step, for each pixel, we scale values into the range 0-1. The Normalization is used to make model training less sensitive to the scale of features. This allows our model to converge to better weights and, in turn, leads to a more accurate model.

3.2 System model construction

In this phase, we focus on building the system model. These models consist of two parts, a feature extractor, and a classifier. The feature extractor is chosen from the five proposed pre-trained models. The classifier was chosen as the best of the 3 types of classifiers. Based on the results of prediction models.

the matching function introduces a suitable person where the making decision step decides that person is male/female and Age group Male/female.

3.2.1 Feature extractor

In this step, we focus on the representation of the proposed HBFTs schema. The figure 3.11 shows the general architecture of HBFTs, Firstly, we present a simple schema for each classification.

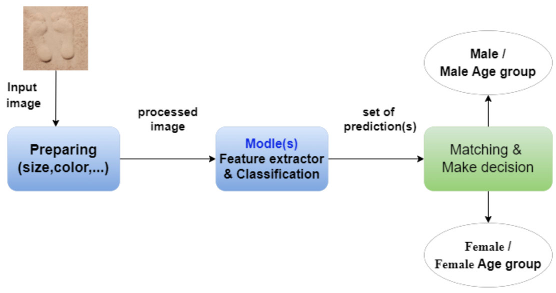


Figure 3.11: General architecture of HBFTs.

3.2.1.1 HBFT system schema

In this part, we present two schemas for our proposed HBFTs schema. The first schema is based on the BMC schema that has one model and the second schema is based on the MMC schema which has 5 models.

3.2.1.1.1 binary Model classification schema The figure 3.12 shows the HBFTs schema of BMC which illustrates the main parts of working the system, dataset preparation, CNNs features extractor, classifier, matching, and making decisions.

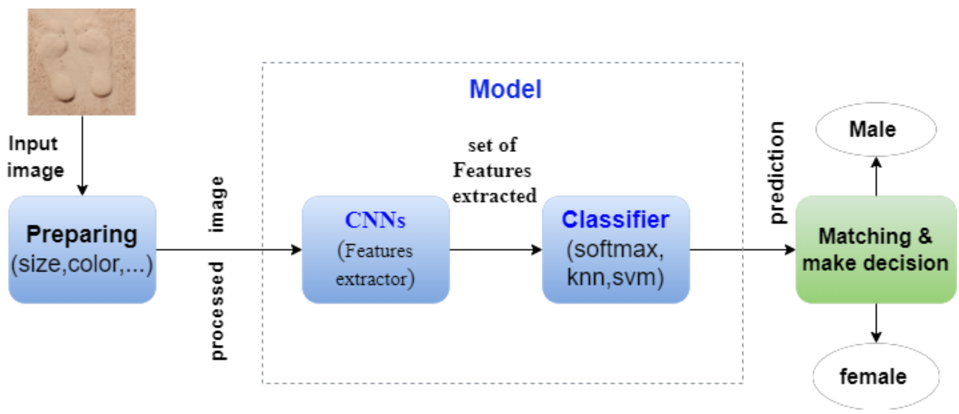


Figure 3.12: The HBFTs schema of BMC.

In the above schema, we notice that this classification Model includes only one model which consists of CNNs and a classifier, where CNNs for extracting the image feature, and a classifier for performing the task of classification and giving a prediction result.

3.2.1.1.2 Multi-model classification schema The figure3.13 shows the HBFTs schema for the MMC, which illustrates the main parts of the system, dataset preparation, CNNs features extractor, classifier, matching, and making decisions.

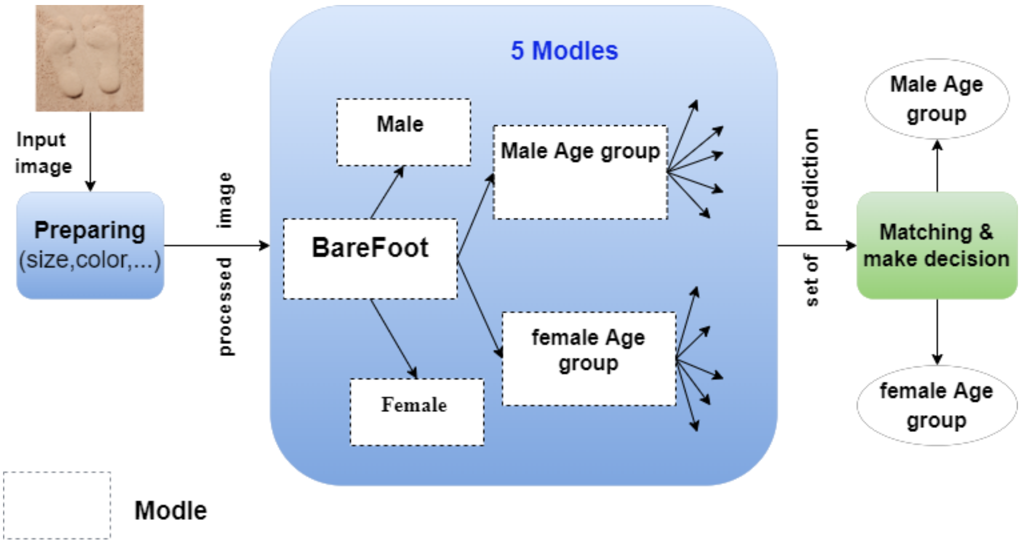


Figure 3.13: The HBFTs schema for the MMC .

In the previous schema, we notice that this approach includes five models (5 models). Each model consists of CNNs and a classifier, where CNN's for extracting the image feature, and a classifier for performing the task of classification and giving a prediction result. It is to note that the process of applying these models is in the form of a hierarchical taxonomy, i.e. the determined model to be applied later, depending on the prediction result of the previous model.

3.2.1.1.3 feature extractor selecting In this part, we decided to use the CNNs model as a feature extractor, For this, we chose the VGG16 model for the feature extraction step. we use the softmax layer as a classifier. with the parameters:

- input size: 224 x 224.
- without augmentation data.
- Training data: 80%.
- Validation data: 10%.
- Testing data: 10%.
- Batch size (BS) : 32.

Figure3.14 shows the feature extractor CNNs in the VGG16 model (freezing CNNs of VGG16).

3.2.2 Classification

Previously, we have only focused on feature extractor. In this step, we focus on the classifier which has many types. For the VGG16 pre-trained models, for extracting

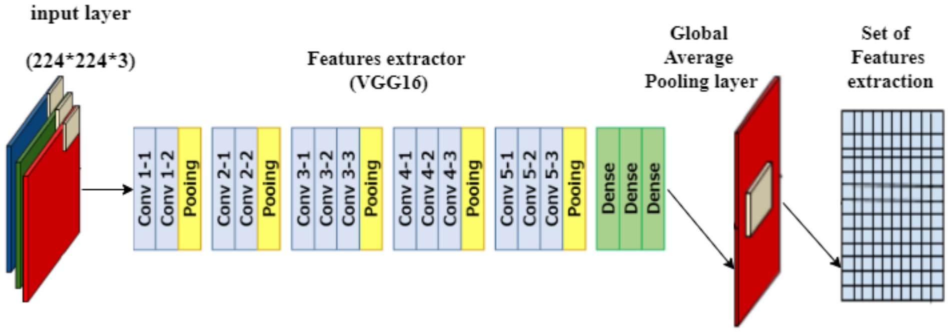


Figure 3.14: Features extractor CNNs in the VGG16.

features from the pictures dataset, we used a VGG16 pre-trained model, and we replaced the last layer of the VGG16, which simply takes a probability for each of the 1000 classes in the ImageNet, with a layer that takes N probabilities, where N is the number of labels for a dataset. Furthermore, we freeze the weights of each layer in the VGG16 model so that they do not train, as we want our feature extractor to remain unchanged. Then, relating this freezing layer (untrainable layer) with the softmax layer (trainable) for classification. After that, we applied the training on the produced CNNs architecture (freezing layer with softmax layer) to train the classifier on the features extracted from the freezing layer. This method is called ***transfer learning.***

Each model architecture consists of two parts, feature extractor layers in the VGG16 model and a classifier as shown in figure3.15.

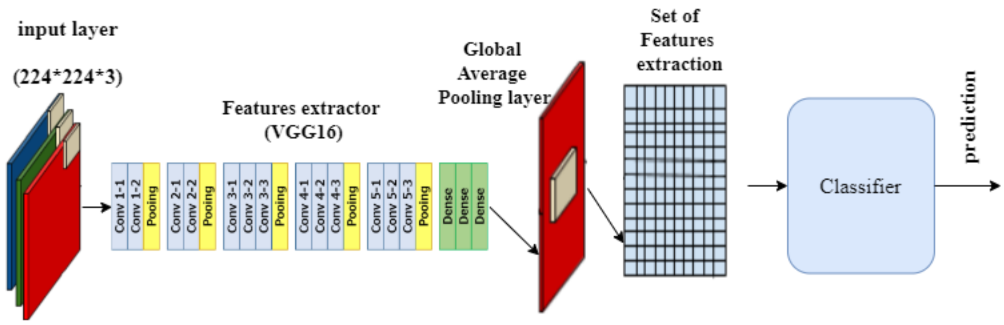


Figure 3.15: Model architecture.

From the previous architecture, we notice that the model consists of 2 parts. The first part represents a feature extractor layer in the VGG16 model (freezing weights). The second part represents a classifier (Softmax), we distinct case of the model as shown in the figure3.16.

- 1. Model case: VGG16 feature extractor with a Softmax classifier.

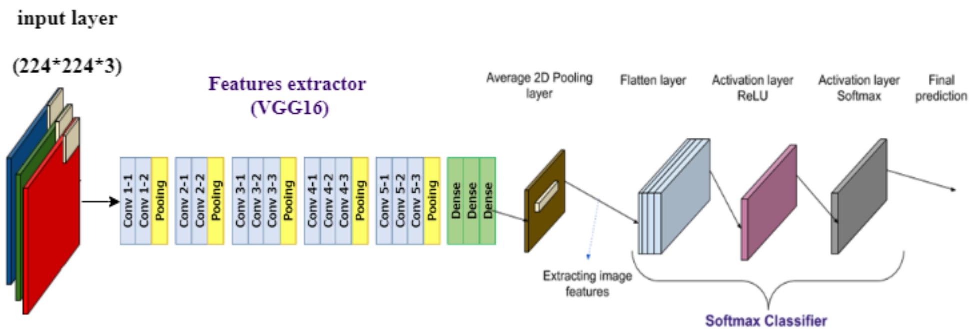


Figure 3.16: Model case1 (Softmax).

3.2.3 Matching

The matching stage involves comparing the obtained results to existing data. We describe the proposed matching algorithm in Algorithm to look for a degree of congruence between the expected information from the model(s) and the information of a person who has been recognized by the system previously.

3.2.4 Making a decision

after the matching function is completed, We get the most likely person with the information and their score of matching. So, based on the score and likelihood of the prediction model, we can determine if the input image is male or female, as well as the age group to which it belongs.

Conclusion

in this chapter, we proposed system architecture for recognizing HBFT.
Firstly, we collected and processed our dataset, then built datasets for the model to be trained in our proposed system. Also, we explained the most important steps for building and training the model. In the next chapter, we will discuss the results of implementing this proposed HBFT system.

Chapter 4

Results and discussions

Introduction

After we have seen dataset preparation, systems architectures in the precedent chapter. This chapter will introduce the tools chosen for system development . In addition, we will present the test results in detail. Finally, we discuss the results obtained to decide system accuracy value. We wrapped up our research by demonstrating the interfaces for a web application.

4.1 Implementation tools

In this section, we present the important development tools that we used in our work. . We begin by discussing the development tools in general. After that, we will explain the programming language, working environment, API Framework, and the most significant libraries utilized, as well as the operating system.

These tools are used in two phases, the training phase, and the deployment phase, as follows:

- ***Phase 1:*** training models, the principal language of programming used is Python3 in the Environment Co-laboratory by using the TensorFlow2.x library to train and test the models. Besides, we used the Drive cloud to upload the dataset from it (Mount Drive) to the colab environment for training.
- ***Phase 2:*** deployment, loading models, and using it as a developed web application.

we used the next set of tools for the development of web application:

- Front-end: HTML5, CSS3, JS3.
- Back-end: Python 3.9.12.
- Library: TensorFlow 2.8.0.
- API Framework: Flask 1.1.1.
- Environment: Spyder (anaconda3) 5.1.5 .

We are working on Windows, on one laptop Has the following characteristics:

- Windows 10. Home.
- Processor Intel Core™ i5-4300U CPU @ 1.90GHz (4 CPUs), 2.5 GHz.
- Graphics Intel HD Graphics Family.
- OS type 64-bit.

So, we explain important development tools that are mentioned previously, which are: Python,Spyder, Colab, Keras, TensorFlow, Jupyter Notebook ,Flask, HTML, CSS, JS.

- ***Python:***

  Python is a high-level programming language used for general programming. Created by Guido van Rossum and released in 1991, Python has a design philosophy that emphasizes the readability of the code, including using virtual spaces. It provides constructions that allow explicit programming at a small and large scale. Python has a dynamic gadget and automated reminiscence management. It helps more than one programming paradigm, inclusive of object-oriented, imperative, functional, and procedural, and has a complete general library. Python interpreters are reachable for many running structures [31].

Figure 4.1: python logo [34].

- ***Spyder:***

  Spyder is a free and open source scientific environment written in Python, for Python, and designed by and for scientists, engineers and data analysts. It features a unique combination of the advanced editing, analysis, debugging, and profiling functionality of a comprehensive development tool with the data exploration, interactive execution, deep inspection, and beautiful visualization capabilities of a scientific package [37].

Figure 4.2: Spyder logo [37].

- ***Colab:***

  Google Colab is a free cloud service that now supports free GPUs, improving coding skills in the Python programming language. Develop in-depth learning applications using popular libraries such as Keras, TensorFlow, and PyTorch. The most important feature that distinguishes Colab from other free cloud computing services is: that Colab provides a GPU and is entirely free. Colab is a free and hosted Jupyter notebook environment that requires no setup to use and runs entirely in the cloud (by the browser), it was created to help disseminate machine learning education and research. Colab hardware available [27, 31]:

  - Accelerator GPU: up to Tesla K80 with 12 GB of GDDR5 VRAM, Intel Xeon Processor with 2cores @2.20 GHz, RAM 13 GB.
  - Accelerator TPU: Cloud TPU with 180 teraflops of computation, Intel Xeon Processor with 2cores @2.30 GHz, RAM 13 GB.
  - Processor: CPUs Intel Xeon Processor with 2cores @2.30 GHz, RAM 13 GB.
  - Disk: 68,40 GB free space.
  - RAM: 12,72 GB free space.

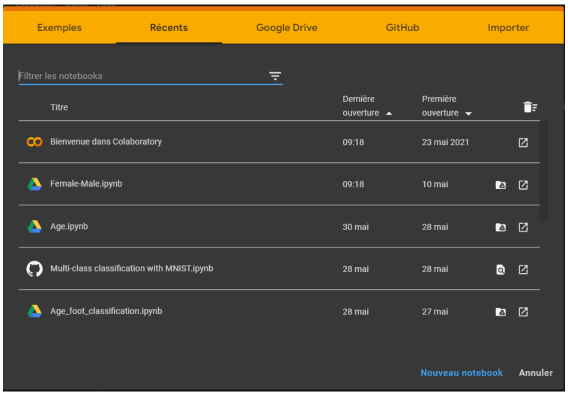


Figure 4.3: Google Colab Environment.

- ***Jupyter Notebook:***

  The Jupyter Notebook is an open-source net utility that lets you create and share files that comprise stay code, equations, visualizations, and narrative textual content. Uses include data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and much more [31].

Figure 4.4: Jupyter Notebook logo [29].

- ***TensorFlow:***

  TensorFlow is an open-source framework was created by the Google Brain team to research Machine Learning and Deep Learning. It is considered a modern version of Theano. it's designed to streamline the process of developing and executing advanced analytics applications for users such as data scientists, statisticians, and predictive modelers[31, 44].

- ***Keras :***

  Keras is an open-source library, the highest level, and the most user-friendly framework. It allows users to choose whether the models they build are running on Theano or TensorFlow or PlaidML and others. The library was developed to be modular and user-friendly [26].

- ***Drive:***

  Google Drive is a free cloud-based storage service developed by Google, that enables users to store and access files online which get 15 GB of space in Drive for free. The service syncs stored documents, photos, and more across all of the user's devices, including mobile devices, tablets, and PCs.
  Google Drive integrates with the company's other services and systems – including Google Docs, Gmail, Android, Chrome, YouTube, Google Analytics, and Google+. Google Drive competes with Microsoft OneDrive, Apple iCloud, Box, Dropbox, and SugarSync. its main purpose is to expand the ability to store files beyond the limits of the local hard drive [12].

- ***Flask:***

  It is a web framework written in Python and built on Werkzeug's tools and the Jinja2 template engine. this means flask provides us with tools, libraries, and technologies that allow us to build a web application. Flask is also called a mini framework because it doesn't require any tools or libraries in particular.

- ***HTML:***

  HTML (HyperText Markup Language) is the most basic building block of the Web. It defines the meaning and structure of web content. Other technologies besides HTML are generally used to describe a web page's appearance/presentation (CSS) or functionality/behavior (JavaScript) [23].

- ***CSS:***

  CSS is the acronym for "Cascading Style Sheets", it is a computer language for laying out and structuring web pages (HTML or XML). This language contains coding elements and is composed of these "cascading style sheets" which are equally called CSS files (.css) [10].

- ***JS:***

  JavaScript is a scripting or programming language that allows you to implement complex features on web pages and create dynamically updating content, control multimedia, and animate images [28].

4.2 Implementation results

In this part, we implement the experiment on the model for our system, which passes by two phases, a training phase, and a testing phase. The training phase is to train the architecture model on a specific dataset, and the testing phase is to know the accuracy of the trained model. After starting the implementation, we define some configuration arguments with constant values in the model:

- Training data: 80%.
- Validation data: 10%.
- Testing data: 10%.
- Batch size (BS): 32.
- Optimizer: Adam().

These parameters will apply in the model, with the split of the dataset (training, testing, validation) that will be the same splitting.

The table 4.1 below presents the values of splitting each dataset into 3 sets, training, testing, and validation.

Table 4.1: the values of splitting each dataset to 3 sets, training, testing, validation.

Dataset	Dataset size 100%	Training set 80%	Testing set / Validation set 20%
binery	1160	928	232
Gender	1160	928	232
Male Age group	409	284	125
Female Age group	749	523	226

4.2.1 Training phase

The training phase is the most important phase, which trains the proposed model architecture, VGG16 (features extractor CNNs) with classifier (Softmax). and They are for the classifier only (CNN extractor features are not trainable). After training the classifier of each classification, we get 6 trained models (one for BMC and 5 for MMC) for each case.

In our work, we proposed 2 different classifications so we trained the model(s) of each classification on its training dataset, as follows:

For binary Model classification, the proposed classification architecture was trained by the Barefoot dataset. while the Multi-Model classification is trained as follows:

- the proposed Male/Female architecture is trained by the Barefoot dataset.
- the proposed Barefoot Age group architecture is trained by the Male Age group dataset.
- the proposed Barefoot Age group architecture is trained by the Female Age group dataset.

4.2.2 Testing phase

In the previous phase, we get a set of trained models. For examining the validity of each model, we test these models on its testing dataset. The factor used is accuracy as an evaluation metric. The results of the testing phase are shown in Table 4.2, for each classification in the case of the classifier (Softmax).

Table 4.2: results of the testing phase for each classification .

Name model	**Number of classes**	**Epoch**	**Accuracy for Softmax Classifier**
binary	2	100	97%
Gender	2	100	97%
Male Age group	5	100	96%
Female Age group	5	100	96%

Through the table above, we can see so clearly the important results that help us to decide the best accuracy value for our system. Whith the biray model classification the accuracy for the softmax classifier is 97%. While with the Multi-Model classification the accuracy for the softmax classifier is 96%. In the MMC, the accuracy of the models was taken as the average accuracy of each of them.

4.3 Results discussion

According to the previous results and analysis of these results: in multi-model classification, we got a 96% accuracy value and in binary model classification, we got a 97% accuracy value using a softmax classifier. Therefore, we can say that the accuracy of our system is 96.50%.

4.4 Application interface

In this portion, we set our work in an integrated and directly usable application. First, we save and load the selected models in the application (web). Then, we developed an application suitable for these models.

the figure 4.5 is shown The Home interface for a web application.

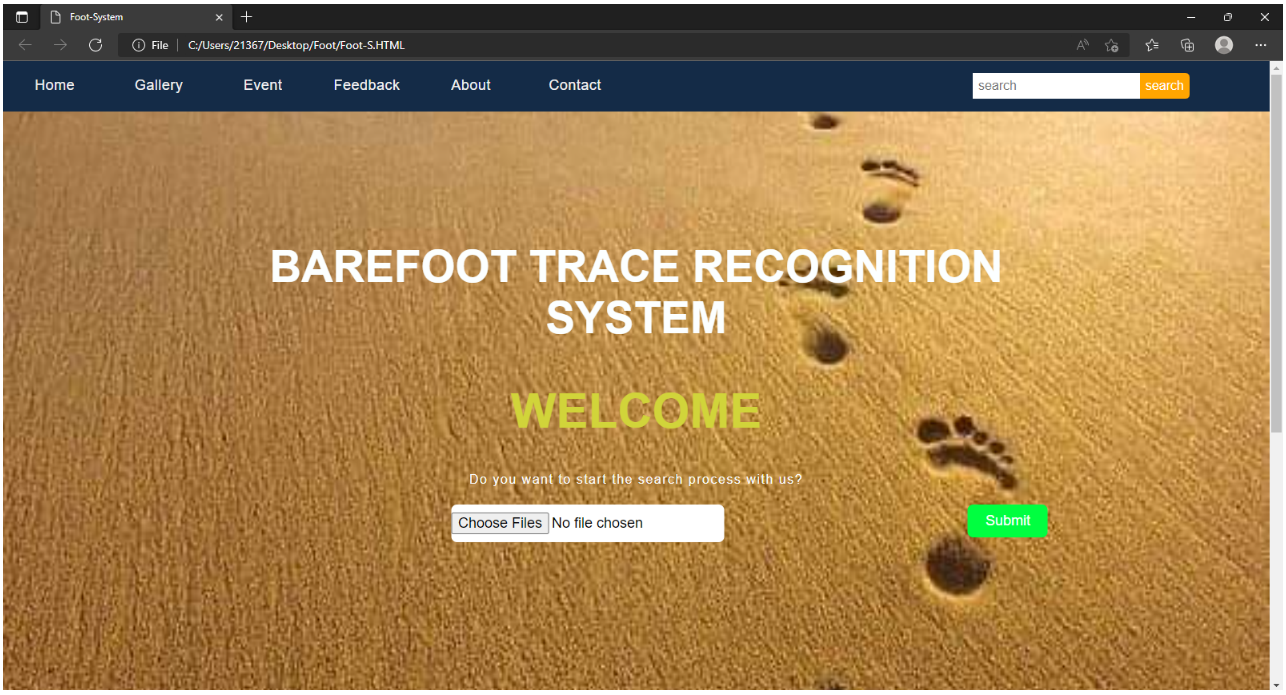


Figure 4.5: Home interface for web application.

Conclusion

In this chapter, we presented the development tools for training and testing our proposed system for human Barefoot trace recognition, and discussed and evaluated the results.

Conclusion and perspectives

In this work, we proposed a system, that recognizes images of the human Barefoot traces. For that, We trained a convolutional neural network that predicts age and gender from a given image containing a person's footprint by using a CNN model for extracting the image's features. the model is composed of two parts, a pre-trained model and a classifier. The pre-trained VGG16 model was chosen for integration into the system classifier (Softmax). Where the system was working efficiently and we eventually obtained satisfactory results, with an accuracy of 96.5%.

However, several obstacles and challenges was faced during the work, and it would be very beneficial to solve them for improving system performance. These difficulties can be classified as follows:

- Dataset images: splitting the dataset into smaller subsets decreases the number of images used for training as well as for testing, which makes the accuracy low during train or test. As a result, we obtain a poor model, and consequently a poorly trained system.
- Handling many models: the number of models influence directly the performance of the system because it consumes more processing time and more storage space. Which means that its structure and data size must be deeply studied.

In the future, the system can be improved by adding more data to its models and balancing the data in each class for any dataset, or by changing its architecture.

In conclusion, we say that the importance of the program lies in the benefit it provides to humans, and we ask God To help us perform our work to the fullest extent, and we hope that we have provided by our work even a small benefit.

Bibliography

[1] J. Brownlee – “What is Deep Learning?”, https://machinelearningmastery.com/what-is-deep-learning/, 2019, [Updated on August 14, 2020].

[2] V. Cerqueira, L. Torgo et C. Soares – “Machine learning vs statistical methods for time series forecasting: Size matters”, *arXiv preprint arXiv:1909.13316* (2019), p. 375–387.

[3] S. Chatterjee – “ What is Feature Extraction? Feature Extraction in Image Processing”, https://www.mygreatlearning.com/blog/feature-extraction-in-image-processing/, 2021, [updated Oct 29, 2021].

[4] N. S. Chauhan – “Model Evaluation Metrics in Machine Learning”, https://www.kdnuggets.com/2020/05/model-evaluation-metrics-machine-learning.html, May 28, 2020, [updated May 28, 2020].

[5] T. Contributor – “ machine vision (computer vision)”, https://www.techtarget.com/searchenterpriseai/definition/machine-vision-computer-vision, 2016, [updated in July 2016].

[6] deeplizard – “ Deep Learning Fundamentals - Classic Edition”, https://deeplizard.com/learn/video/5T-iXNNiwIs, 2017, [Online; accessed November 22, 2017].

[7] N. Dong, L. Zhao, C.-H. Wu et J.-F. Chang – “Inception v3 based cervical cell classification combined with artificially extracted features”, *Applied Soft Computing* **93** (2020), p. 106311.

[8] F. H. Dr. Kewal Krishan, PhD – “Support bare footprint metric analysis methods for comparison and identification in forensic”, Tech. report, Department of Anthropology, (Centre for Advanced Studies in Anthropology) Panjab University, Chandigarh-160 014, India ", May 2018.

[9] — , “Forensic review paper on various methods used in forensic podiatry”, Tech. report, Karunya University, January 2021.

[10] J. Duckett – *Html & css: design and build websites*, vol. 15, Wiley Indianapolis, IN, 2011.

[11] M. P. Ekstrom – *Digital image processing techniques*, vol. 2, Academic Press, 2012.

[12] I. W. Erica Mixon – “ Google Drive”, https://www.techtarget.com/searchmobilecomputing/definition/Google-Drive, 2018, [Online; accessed March 2022].

[13] A. Eva – “Artec 3D scanners help police identify footprints at crime scenes”, https://www.artec3d.com/cases/identifying-footprints-forensics-21st-century, 2022, [Online accessed june 3, 2022].

[14] M. Fabien – “XCeption Model and Depthwise Separable Convolutions”, https://maelfabien.github.io/deeplearning/xception/#, March 20, 2019, [updated March 20, 2019].

[15] F. C. Hanmei Hong, Mingchuan Zhou – “Detection of melanotic cooked shrimp using computer vision”, Tech. report, International Agricultural Engineering Journal, December 2016.

[16] P. Huilgol – “Top 4 pre-trained models for image classification with python code”, https://www.analyticsvidhya.com/blog/2020/08/top-4-pre-trained-models-for-image-classification-with-python-code/, 2020, [updated August 18, 2020].

[17] B. Javidi – *Image recognition and classification: algorithms, systems, and applications*, CRC press, 2002.

[18] T. Jiang, J. L. Gradus et A. J. Rosellini – “Supervised machine learning: a brief primer”, *Behavior Therapy* **51** (2020), no. 5, p. 675–687.

[19] D. Johnson – “ Supervised Machine Learning: What is, Algorithms with Examples”, https://www.guru99.com/supervised-machine-learning.html#1, 2022, [Updated May 14, 2022].

[20] — , "Difference Between Deep Learning and Machine Learning Vs AI", https://www.guru99.com/machine-learning-vs-deep-learning.html, 2022, [Updated May 14, 2022].

[21] Knoldus – " Architecture of Artificial Neural Network)", ArchitectureofArtificialNeuralNetwork, 2022, [Published May 3, 2022].

[22] O. Kramer – "K-nearest neighbors", Dimensionality reduction with unsupervised nearest neighbors, Springer, 2013, p. 13–23.

[23] J. Krause – "Html: hypertext markup language", Introducing Web Development, Springer, 2016, p. 39–63.

[24] J. Lawrence – *Introduction to neural networks*, California Scientific Software, 1993.

[25] Y. H. Liu – "Feature extraction and image recognition with convolutional neural networks", *Journal of Physics: Conference Series*, vol. 1087, IOP Publishing, 2018, p. 062032.

[26] J. Moolayil, J. Moolayil et S. John – *Learn keras for deep neural networks*, Springer, 2019.

[27] A. S. R. L. Nadjah – *Development of human foot trace recognition system*, Mémoire, UNIVERSITÉ ECHAHID HAMMA LAKHDAR - D'EL OUED, 2020.

[28] R. Nixon – *Learning php, mysql & javascript*, " O'Reilly Media, Inc.", 2021.

[29] J. Notebook – "Jupyter notebook", https://jupyter.org/, 2022, [Online accessed June 11, 2022].

[30] Omdena – " Top 10 Machine Learning Examples in Real Life (Which Make the World a Better Place)", https://omdena.com/blog/machine-learning-examples/, 2022, [Published May 3, 2022].

[31] B. O. B. Oussama – *Solar radiation prediction using machine learning*, Mémoire, UNIVERSITÉ MOHAMED BOUDIAF - M'SILA, 2020.

[32] S. J. Pan – "Transfer learning", *Learning* **21** (2020), p. 1–2.

[33] C. Patrick Grieve – "Deep learning vs. machine learning: What's the difference?", https://www.zendesk.com/blog/machine-learning-and-deep-learning/, January 23, 2020, [updated March 8, 2022].

[34] python – "python", https://www.python.org/, 2022, [Online accessed June 11, 2022].

[35] S. Ray – "Understanding Support Vector Machine(SVM) algorithm from examples (along with code)", https://www.analyticsvidhya.com/blog/2017/09/understaing-support-vector-machine-example-code/, 2017, [published on Oct 6th, 2015].

[36] M. T. Samba Raju Chiluveru – "Low snr speech enhancement with dnn based phase estimation", Tech. report, International Journal of Speech Technology, March 2019.

[37] spider – "spyder", https://www.spyder-ide.org/, 2022, [Online accessed June 11, 2022].

[38] R. Szeliski – *Computer vision: algorithms and applications*, Springer Science & Business Media, 2010.

[39] S. Tammina – "Transfer learning using vgg-16 with deep convolutional neural network for classifying images", *International Journal of Scientific and Research Publications (IJSRP)* **9** (2019), no. 10, p. 143–150.

[40] T. H. E. Team – " Foot", https://www.healthline.com/human-body-maps/foot#1, 2018, [Updated on January 21, 2018].

[41] R. Z. Tiago Carvalho, Edmar Rezende – "Deep feature-based classifiers for fruit fly identification (diptera: Tephritidae)", Tech. report, Institute of Science and Technology, October 2018.

[42] M. Toolan – "Toward a semi-automatic method of barefoot measurement", Tech. report, University of Lincoln, March 2019.

[43] A. Varangaonkar – " Top 5 Deep Learning Architectures", https://hub.packtpub.com/top-5-deep-learning-architectures/, 2018, [published on July 24, 2018 - 6:00 pm].

[44] J. Vaughan – " TensorFlow", https://www.techtarget.com/searchdatamanagement/definition/TensorFlow, 2018, [Online; accessed February 2022].

[45] L. A. Vincenzo Taormina, Donato Cascio et G. Raso – "Performance of fine-tuning convolutional neural networks for hep-2 image classification", Tech. report, , University of Palermo, October 2020.

[46] L. Wen, X. Li et L. Gao – “A transfer convolutional neural network for fault diagnosis based on resnet-50”, *Neural Computing and Applications* **32** (2020), no. 10, p. 6111–6124.

[47] J. Yang et J. Li – “Application of deep convolution neural network”, *2017 14th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP)*, IEEE, 2017, p. 229–232.

[48] F. Zhuang, Z. Qi, K. Duan, D. Xi, Y. Zhu, H. Zhu, H. Xiong et Q. He – “A comprehensive survey on transfer learning”, *Proceedings of the IEEE* **109** (2020), no. 1, p. 43–76.