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Abstract

Neural networks are a set of algorithms whose operation is inspired by biological neurons, these networks have been developed to solve problems: control, recognition of shapes or words, decision, and memorization, in this work a new type of neural networks was used which is the convolutional neuron network for Classification of banknotes according to their fitness so we proposed an architecture, used two pretrained models and made comparisons, in order to obtain good results.

ملخص

الشبكات العصبية هي مجموعة من الخوارزميات التي تستلهم عملياتها من الخلايا العصبية البيولوجية، وقد تم تطوير هذه الشبكات لحل المشكلات: التحكم، والتعرف على الأشكال أو الكلمات، والقرار، والحفظ، وفي هذا العمل تم استخدام نوع جديد من الشبكات العصبية وهو شبكة العصبونات التلافيفية لتصنيف الأوراق النقدية حسب لياقتها لذلك اقترحنا بنية، استخدمنا نموذجين مدربين مسبقاً وأجرينا مقارنات من أجل الحصول على نتائج جيدة.

Keywords: Digital image processing, convolutional neural networks CNNs, Banknote fitness.

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Glossary of Acronyms and Abbreviations

AI Artificial Intelligence

ML Machine learning

DL Deep learning

MLP Multi-layer perceptrons

SVM Support Vector Machines

SGD Stochastic Gradient Descent

RMSprop Root Mean Squared Propagation

CNN Convolutional Neural Network

ANN Artificial Neural Network

RNN Recurrent Neural Network

ReLU Rectified Linear Unit

Resnet Residual Neural Network

PCA Principal Component analysis

General introduction

General introduction

In recent years, automatic payment facilities such as vending machines and automatic teller machines have become more and more popular. As a result, the importance of correctly recognizing and classifying banknotes has increased. This problem consists of not only automatically sorting banknotes by denominations, sides, and directions, but also in determining the fitness of those banknotes. The fitness classification of banknotes is concerned with the evaluation of the banknotes' physical conditions, such as staining, tearing, or bleaching. This task helps not only to determine whether a banknote is suitable for recirculation or should be replaced by a new one, but also to enhance the processing speed and sorting accuracy of the counting system.

Problematic

The objective of the thesis is to implement image classification models based on the convolutional neural network and a deep neural network, with different architecture to classify fit and unfit Algerian banknote with denomination of 500DA.

Plans

Chapter I we have presented the fundamentals of image processing and some definitions and we have seen some methods, which help in image processing.

Chapter II, we explain most important techniques in recurrent years, Artificial intelligence, machine learning and deep learning and we discuss about Classification and neural network, and show various type of it then take a look at some Convolutional neural network architecture and transfer learning technique.

Chapter III in this chapter we talked about the state of the art that talks about some studies that dealt with this problem.

Chapter IV is will explain our architectures of the suggested datasets models and describe the tools used in our experiments, with implement simple interface used by Flask, and a discussion over the results of models.

Chapter I Artificial vision

Introduction

Image processing is a technique for applying operations on an image in order to improve it or extract relevant information from it. It is a form of signal processing in which the input is an image and the output is either that image or its characteristics/features.

1. Digital image

The term digital image refers in its most general sense, to any image that has been acquired, processed and saved in a coded form representable by numbers. Digitization is the process of moving from the physical image state, which is characterized by the continuous aspect of the signal that represents, in the image state digital which is characterized by the discreet appearance .It is this digital form that allows subsequent exploitation by computer software tools [12].

2. Digital Image types

2.1. Raster image

Raster images are also known as bitmaps that are comprised of individual pixels of color. Each color pixel contributes to the overall image. It might be compared to pointillist paintings, which are composed with a series of individually colored dots of paint. Each paint dot in a pointillist painting might represent a single pixel in a raster image. When viewed as an individual dot, it is just a color, but when viewed as a whole, the colored dots make up a vivid and detailed painting. The pixels in a raster image work in the same manner, which provides for rich details and pixel-by-pixel editing.

2.2. Vector image

Vector graphics are made up of paths; each with a mathematical formula (vector) that tells the path how it is shaped and what color it is bordered with or filled by. Since mathematical formulas dictate how the image is rendered, vector images retain their appearance regardless of size. They can be scale dinfinitely.

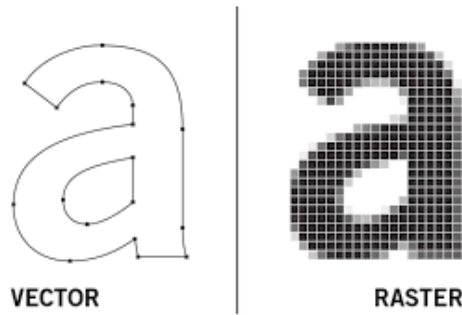


Figure I.1: Raster and Vector image [1]

3. image characteristics

3.1 Pixel

A pixel is the smallest unit of a digital image or graphic that can be displayed and represented on a digital display device. A pixel is the basic logical unit in digital graphics. Pixels are combined to form a complete image, video, text, or any visible thing on a computer display.

A pixel is also known as a picture element (pix = picture, el = element).

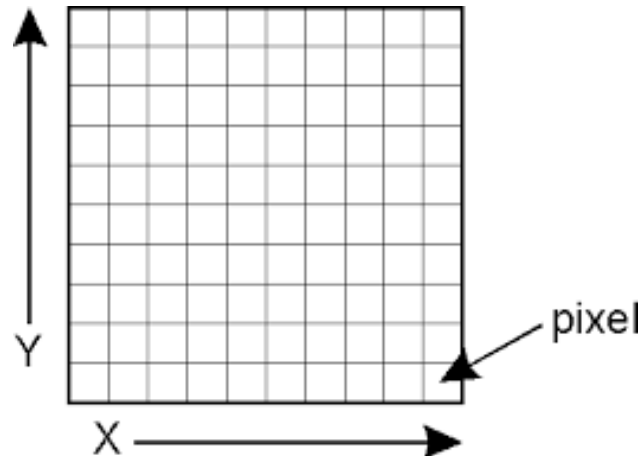


Figure I.2: Digital image[2]

3.2. Color of image

A color image is a digital array of pixel containing a color information. Each image can be decomposed into three different layers according to the three-color channels encoded: Red, Green and Blue.

For instance, an eight bits color images encode the Red and Green channel with three bits and the blue with two. Which could encode 256 different colors.

3.2.1. Type of color Image

Binary Images

It is the simplest type of image. It takes only two values. Black and White or 0 and 1. The binary image consists of a 1-bit image and it takes only 1 binary digit to represent a pixel.

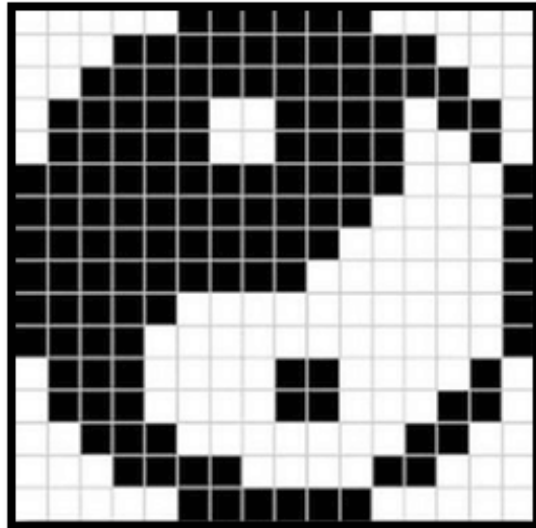


Figure I.3: Binary image[3]

Grayscale images

Grayscale images are monochrome images; it means they have only one color. Grayscale images do not contain any information about color. Each pixel determines available different grey levels. It contains 8 bits/pixel data, which has 256 different grey levels.



Figure I.4: Grayscale image[3]

Color images

Color images are three band monochrome images in which each band contains a different color and the actual information is stored in the digital image. The color images contain gray level information in each spectral band. The images are represented as red, green and blue (RGB images). And each color image has 24 bits/pixel means 8 bits for each of the three color band (RGB).

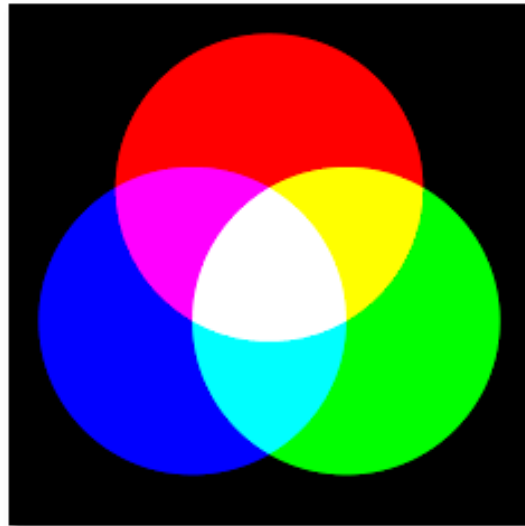


Figure I.5: Color image[3]

3.3. Histograms

A histogram is a graphical representation that organizes a group of data points into user-specified ranges. Similar in appearance to a bar graph, the histogram condenses a data series into an easily interpreted visual by taking many data points and grouping them into logical ranges or bins.

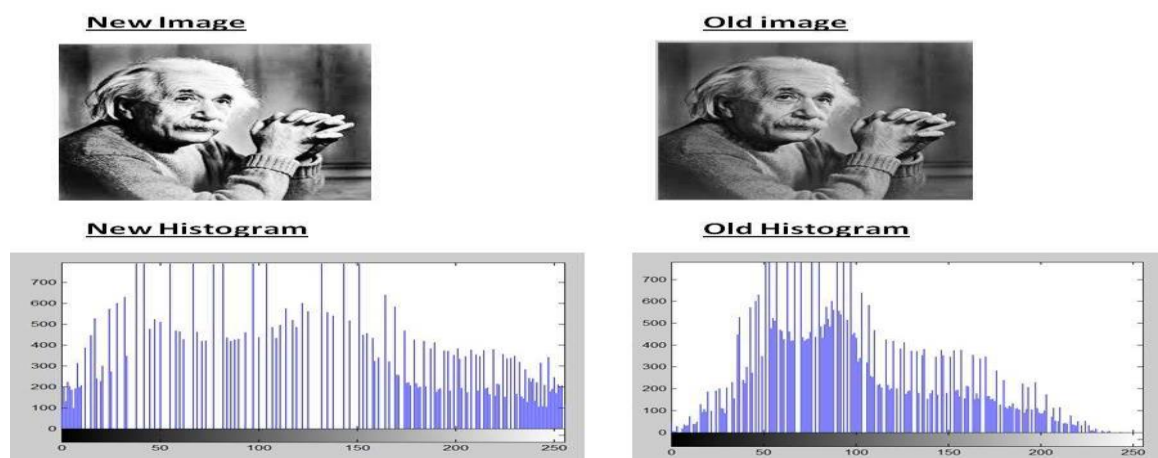


Figure I.6: Example of Histograms[4]

3.4. Resolution

The resolution of an image is the number of pixels contained in the image per unit length. Resolution defines the sharpness and quality of an image. The higher the resolution (i.e. the more pixels in a length of 1 inch), the more accurate the image is in detail.

3.5. Noise

Noise is a random parasitic phenomenon (following a known or unknown probability distribution), it corresponds to disturbances either of the acquisition device or of the scene itself. The sources of noise in an image are:

- Noises related to shooting conditions (shake, scene lighting)
- Sampling noise.
- Noises related to the nature of the scene (dust, scratches).

3.6. Luminance

It is the degree of luminosity of the points of the image. It is also defined as the quotient of the luminous intensity of a surface by the apparent area of this surface, for a distant observer, the word luminance is substituted for the word brilliance, which corresponds to the brightness of an object. A good luminance is characterized by :

- Bright images.
- Good contrast: avoid images where the range of contrast tends towards white or black; these images lead to loss of detail in areas dark or bright.
- The absence of parasites.

3.7. Contour

A contour is materialized by a break in intensity in the image along a given direction. These changes in intensities make it possible to describe significant variations which result in discrepancies in depth, in the orientation of a surface, in the properties of a material and in the lighting of a scene. And by convention we will seek to represent the white contours on a black background (the limit between two pixels).

3.8. The contrast

It is the marked opposition between two regions of an image, more precisely between the dark regions and light regions of this image. The contrast is defined according to the luminance of two image areas. If L_1 and L_2 are the degrees of luminosity respectively of two neighboring zones A_1 and A_2 of an image, the contrast C is defined by the ratio.

3.9. Dimension

This is the size of the image. It is in the form of a matrix whose elements are numerical values representative of the luminous intensities (pixels). The number of rows in this matrix multiplied by the number of columns gives us the total number of pixels in an image.

4. Digital image processing

Digital image processing is the use of a digital computer to process digital images through an algorithm. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of multidimensional systems [13].

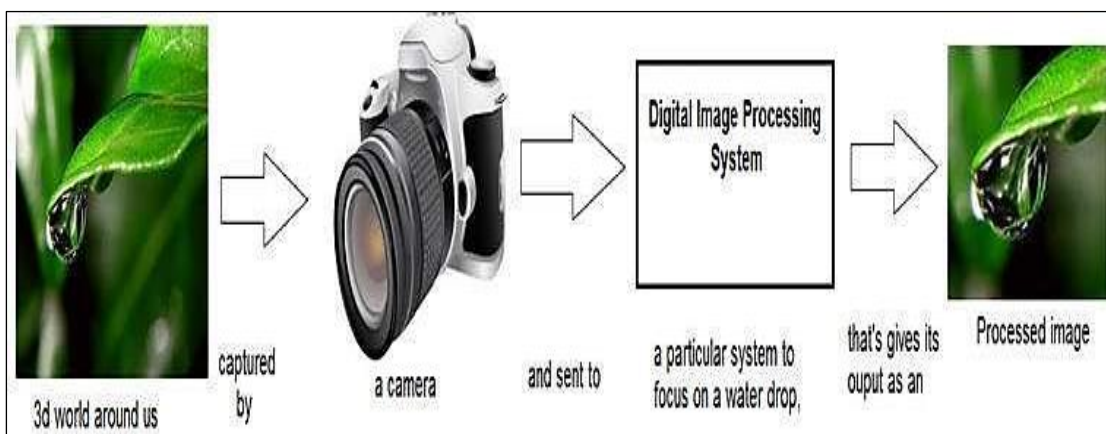


Figure I.7: Image processing[5].

4.1. Fundamental Steps of Digital Image Processing

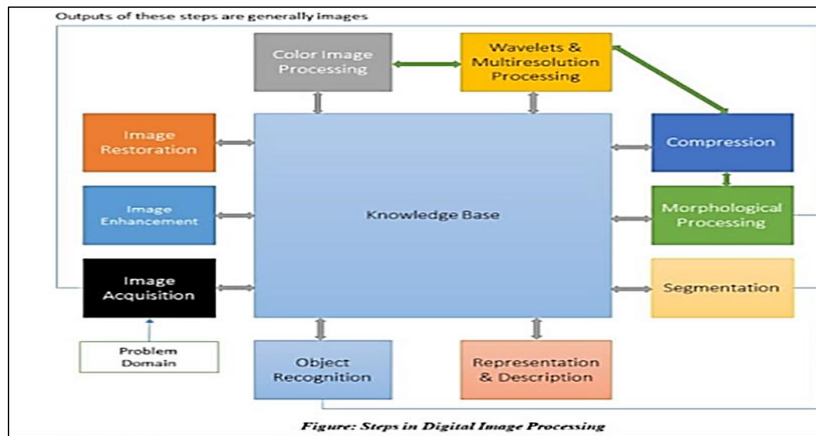


Figure I.8: Steps of Digital Image Processing[6]

4.1.1. Image Acquisition

Image Acquisition is the first step or process of the fundamental steps of digital image processing. It might be as simple as being given an image that has already been converted to digital format. Pre-processing, such as scaling, is usually done during the image acquisition stage.

4.1.2. Image Enhancement

Image enhancement tries to improve the interpretability or perception of information in images for humans, as well as providing 'better' input for other automated image processing approaches. For example, changing the brightness and contrast.



Figure I.9 : Image Enhancement[7]

4.1.3. Image Restoration

The concerns of the image restoration are the removal or reduction of degradations which are included during the acquisition of images e.g.; Noise, pixel value errors, out of focus blurring or camera motion blurring using prior knowledge of the degradation phenomenon. This means it deals with the modelling of the degradation and applying the process (inverse) to reconstruct the image.

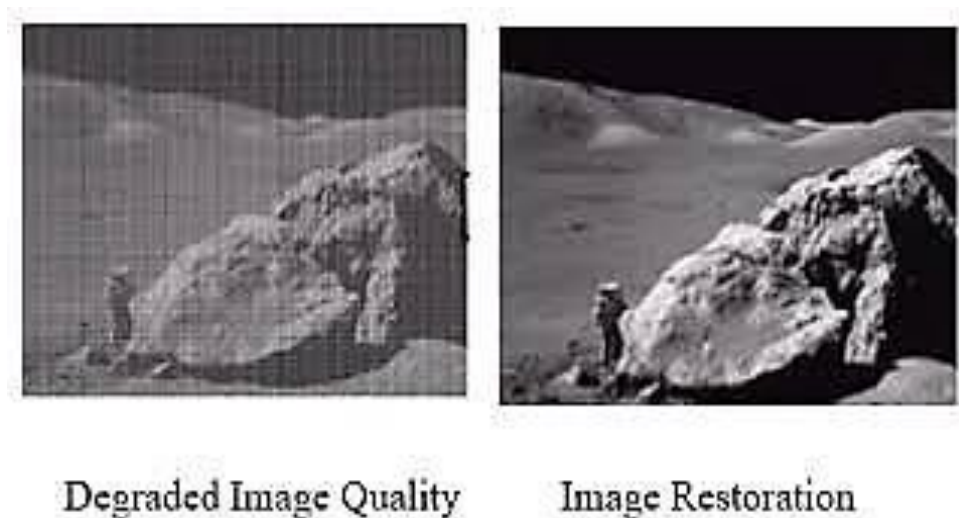


Figure I.10: Image restoration[8]

4.1.4. Color Image Processing

Color image processing is an area that has been gaining its importance because of the significant increase in the use of digital images over the Internet. This may include color modeling and processing in a digital domain.

4.1.5. Image Compression

Compression deals with techniques for reducing the storage required to save an image or the bandwidth to transmit it.

4.1.6. Morphological Image Processing

In morphological processing of images, pixels are added or removed from the images. The structure and shape of the objects are analyzed so that they can be identified.

4.1.7. Segmentation

Segmentation of an image is its partition into disjoint regions, it tries to identify and label the different objects and regions, and there are two basic methods of segmentation: (i) finding the boundary of a region and (ii) finding the interior of a region.

4.1.8. Representation and Description

After an image has been segmented into regions, the resulting aggregate of segmented pixels usually is represented and described in a form suitable for further computer processing. Representing a region involves two choices: (i) represent the region in terms of its external characteristics (its boundary), or (ii) represent it in terms of its internal characteristics (the pixels comprising the region).

4.1.9. Object recognition

Object recognition refers to the process that assigns a label to an object based on its descriptors.

5. Computer vision

Computer vision is the field of computer science that focuses on creating digital systems that can process, analyze, and make sense of visual data (images or videos) in the same way that humans do. The concept of computer vision is based on teaching computers to process an image at a pixel level and understand it. Technically, machines attempt to retrieve visual information, handle it, and interpret results through special software algorithms [14].

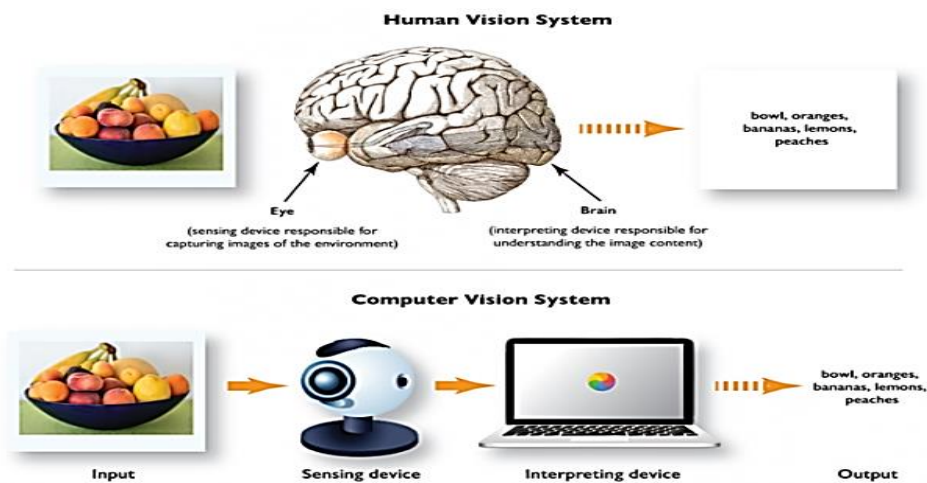


Figure I.11: Computer vision[9]

Common tasks that computer vision systems can be used for:

- **Object classification.** The system parses visual content and classifies the object on a photo/video to the defined category.
- **Object identification.** The system parses visual content and identifies a particular object on a photo/video.
- **Object tracking.** The system processes video finds the object (or objects) that match search criteria and track its movement.

6. Image processing Vs Computer Vision

Computer Vision and Image Processing are both technologies that involve the use of computer programming on images. They can be thought of as two different methods of using computational power to process visual data and there is a lot of overlap between them. Here we present some differences:

Image processing	Computer vision
<ul style="list-style-type: none"> – Image Processing is a subset of computer Vision. – The objective of image processing is to apply a change on the information picture contingent upon the unique situation and the issue is henceforth addressed. – Examples of Image processing denoising, rescaling. 	<ul style="list-style-type: none"> -Computer Vision is a superset of Image Processing. -Computer's Vision will likely comprehend the picture and its content are smoothing. -Example of Computer Vision are Classification, object detection.

Table I.1: Comparison between Image processing and Computer Vision

Conclusion

This chapter has provided some introductory notes on image processing with its Fundamental Steps and we have presented a briefly introduction about computer vision . The future of digital image processing has a high probability to contribute toward the build of smart and intelligent world in terms of health, education, defense, traffic, homes, offices, cities... etc.

Chapter II Artificial Intelligence

Introduction

Artificial Intelligence has grown to be very popular in today's world. It is the simulation of natural intelligence in machines that are programmed to learn and mimic the actions of humans. These machines are able to learn with experience and perform tasks like human.

1. Artificial Intelligence

AI has been defined as a computer-based system designed to perform human-made tasks. According to Russell and Norvig (2009), AI is "a technology that thinks like a human, acts like a human, thinks rationally and acts rationally". It is of great importance to understand what the basic principle of AI is. It can be said that the main principles are reasoning, planning, learning, logic, and perception. The purpose of AI is to build machines that can do tasks that would normally require human intelligence. This technology can process nonlinear relationships, learn, develop and make expert decisions. AI can quickly and reliably analyze vast amounts of data[1].

2. Machine Learning

Machine learning is a type of artificial intelligence (AI) that uses data to extract information. It is also known as predictive analytics or statistical learning, and it is a research subject at the combination of statistics, artificial intelligence, and computer science. In recent years, machine learning approaches have grown increasingly common in everyday life [2].

2.1.Types of Systems of Machine Learning

2.1.1. Supervised learning

Supervised learning is an area of machine learning where the chosen algorithm tries to fit a target using the given input. A set of training data that contains labels is supplied to algorithm. It is based on a massive set of data; the algorithm will learn a rule that is used to predict the labels for new observations. In other words, supervised learning algorithms are provided with historical data and asked to find the relationship that has the best predictive power [3].

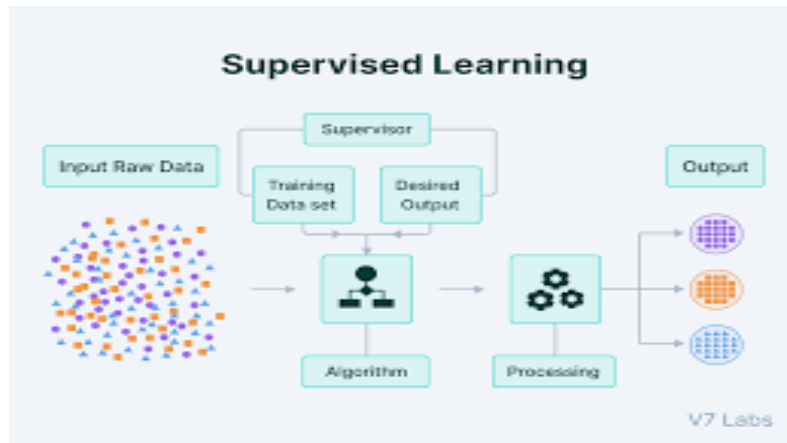


Figure II. 1: Supervised learning[10]

2.1.1.1. Types of supervised Machine learning Algorithms

A. Regression

Regression algorithms predict a continuous value based on the input variables. The primary purpose of regression problems is to calculate a mapping function from the input and output variables. The regression model should be used if your target variable is a quantity such as income, scores, height, or weight, or the probability of a binary category [4].

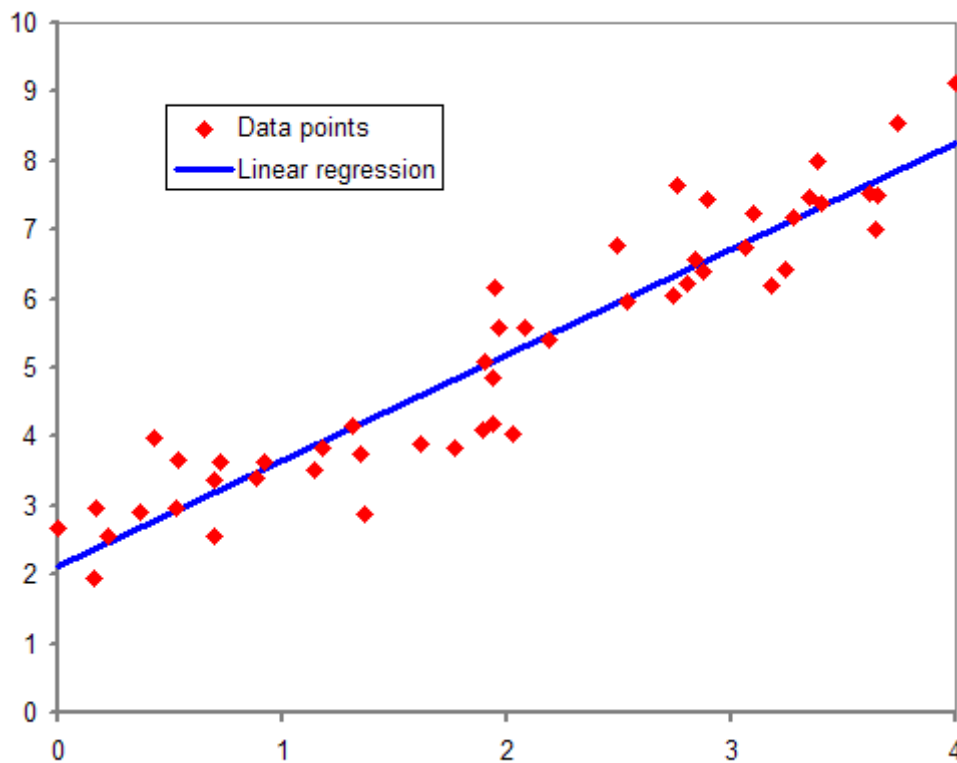


Figure II.2: Regression algorithms[11]

B. Classification

Classification is a prediction model that uses input data to approximate a mapping function to identify discrete output variables, such as labels or categories. Classification algorithms' mapping function is in charge of predicting the label or category of given input data. A classification algorithm can use both discrete and real-valued variables, but it must classify the examples into two or more classes [4].

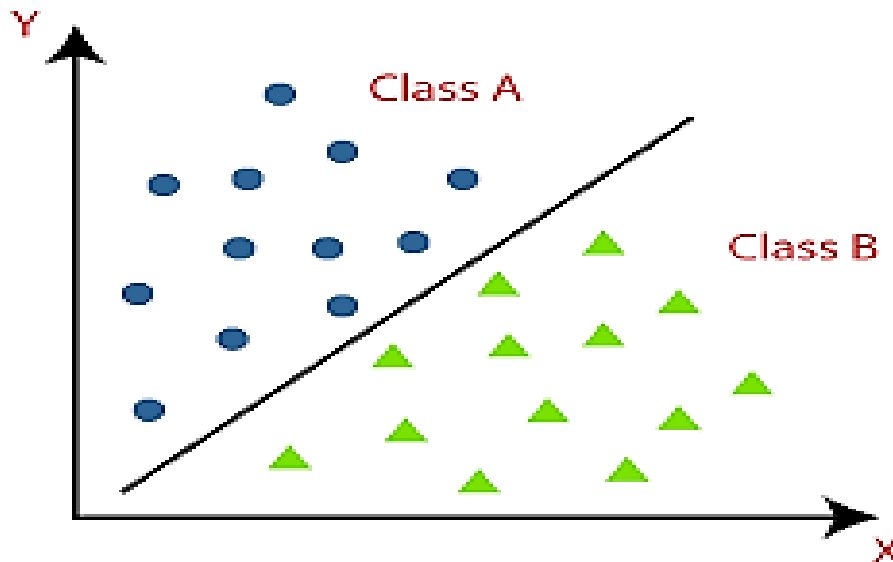


Figure II 3: Classification algorithms[12]

2.1.1.2. Common supervised Learning Algorithms

A. Linear Regression

Linear Regression is a supervised machine learning approach that predicts continuous data. Based on the dependent and independent variables, linear regression predicts an output by fitting the line with the minimum error [18].

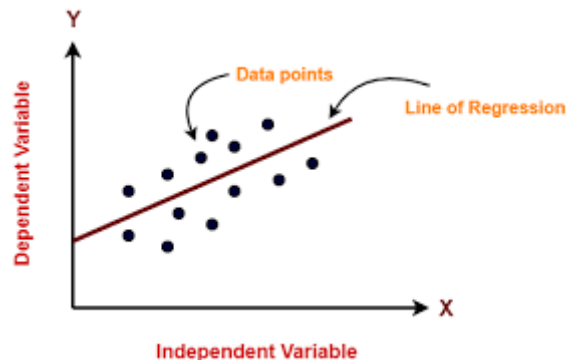


Figure II 4: Linear Regression[13]

B. Logistic regression

Logistic regression is also a supervised machine learning algorithm. Logistic regression is commonly used for classification, as it can output a value that corresponds to the probability of belonging to a given class. In contrast to linear regression, which predicts results as continuous values, logistic regression predicts results as discrete classes [18].

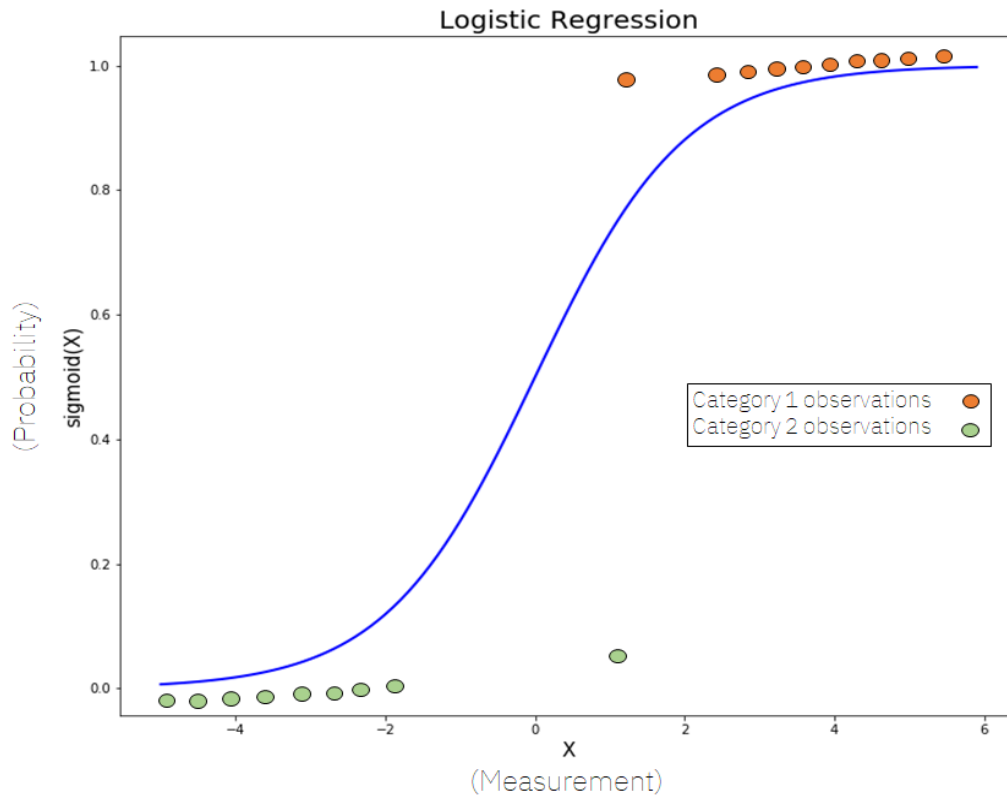


Figure II 5: Logistic Regression[14]

C. Naïve Bayes Algorithm

The Naive Bayes classification algorithm is a supervised machine learning technique that belongs to the classifiers algorithm family. Naive Bayes is a probabilistic classifier based on Bayes theory, which means that it predicts based on an object's probability [18].

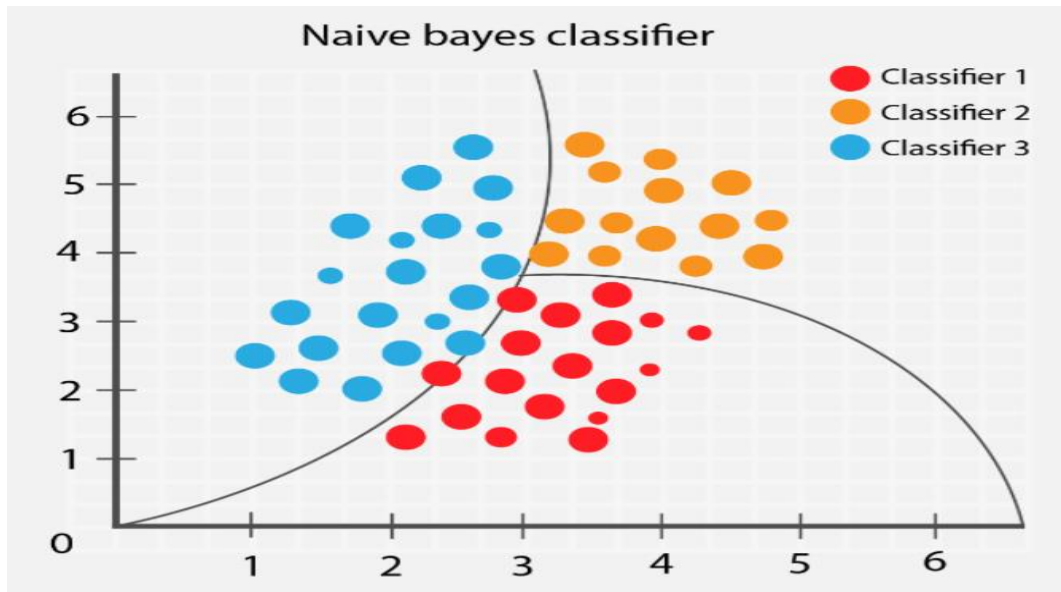


Figure II 6: Naïve bayes[15]

D. Decision Tree Algorithm

Decision trees are supervised machine learning algorithms that can be used for classification and regression tasks. The primary idea behind a decision tree is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. A decision tree works by successively splitting the dataset into small segments until the target variable is the same or until the dataset can no longer be split. But this algorithm is greedy, which makes the best decision at a certain time without regard to global optimally [18].

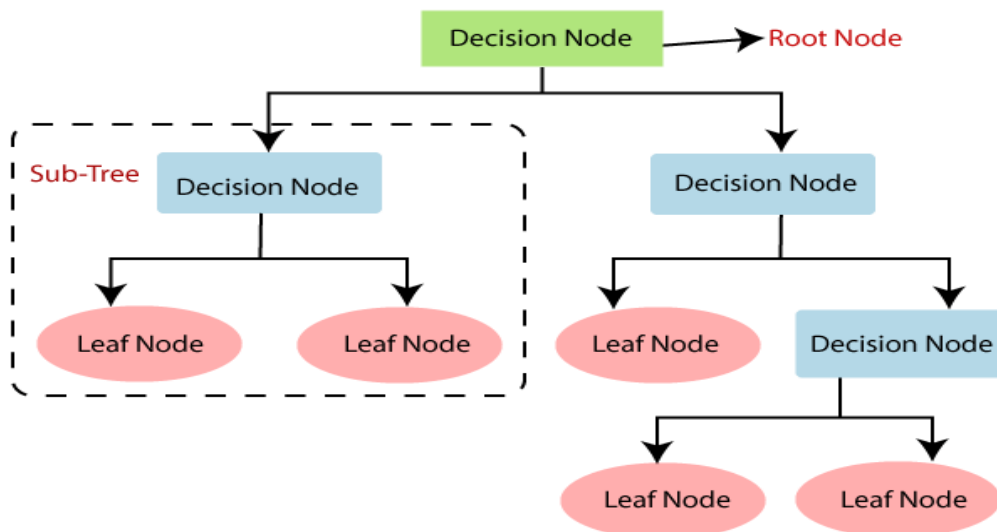


Figure II .7: Decision Tree Algorithm[16]

E. Random Forest Algorithm

Random forest is a machine learning algorithm that is supervised. It is a collection of decision trees that are all slightly different from one another. Random Forests work by training many Decision Trees on different subsets of the features and then averaging their predictions. [18].

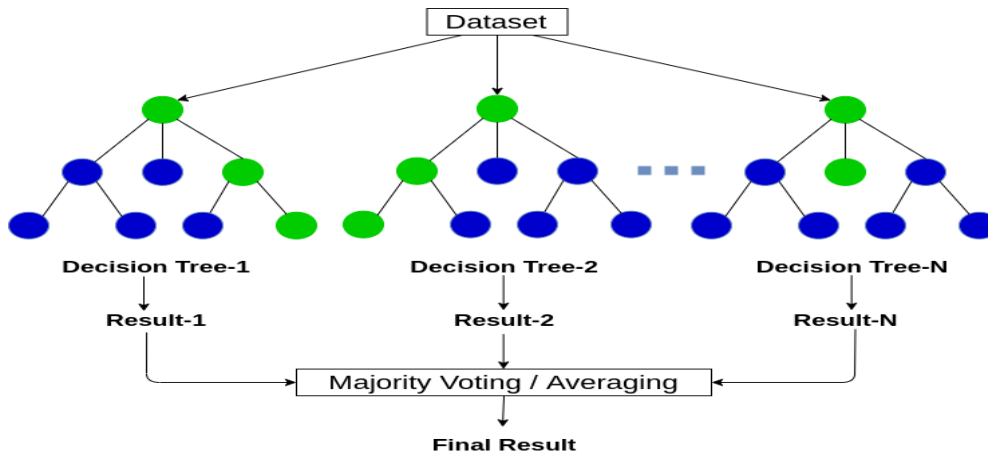


Figure II.8: Random Forest Algorithm[17]

F. K-Nearest Neighbors Algorithm

The K-nearest neighbor (KNN) algorithm is one of supervised machine learning algorithms, and it may be used for both classification and regression. The K-nearest neighbor algorithm's fundamental principle is to find a predetermined number of training samples that are closest to the new point and predict the label using these training samples. The closest data point in the training data set is called its nearest neighbor [18].

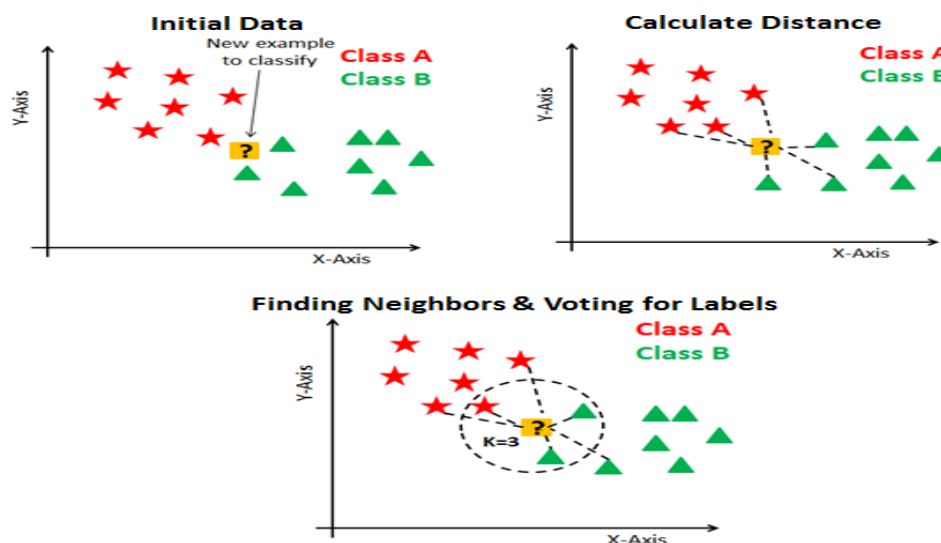


Figure II.9: K-Nearest Neighbors Algorithm[18]

G. Support Vector Machine Algorithm

Support vector machine (SVM) is a supervised machine learning algorithm capable of performing linear or nonlinear classification, regression, and outlier detection. The goal of the SVM algorithm is to learn how important each of the training data points is to represent the decision boundary (*hyperplane*) between the two classes and produces the largest minimum distance (*margin*) between the objects that belong to different classes[18].

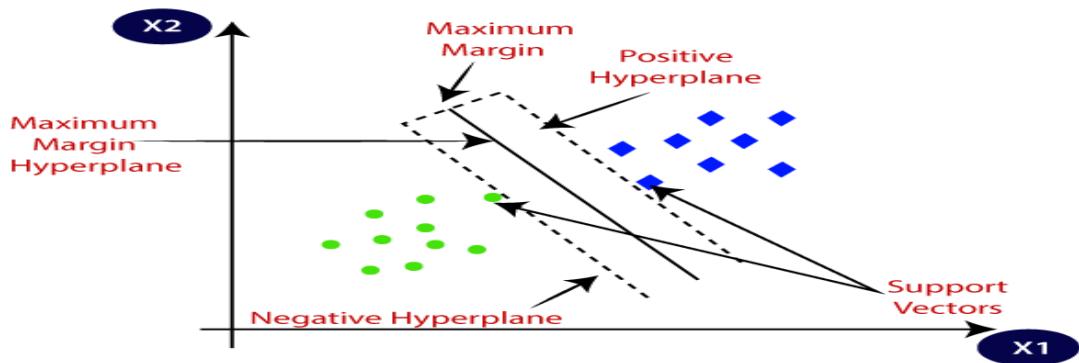


Figure II.10 : Support Vector Machine Algorithm[19]

2.1.2. Unsupervised Learning

Unsupervised learning algorithms attempt to infer patterns from the data without any knowledge of the output the data is meant to yield. This family of models enables for the easy use of larger datasets for analysis and model creation without requiring labeled data, which can be time-consuming and impractical to prepare or obtain [3].

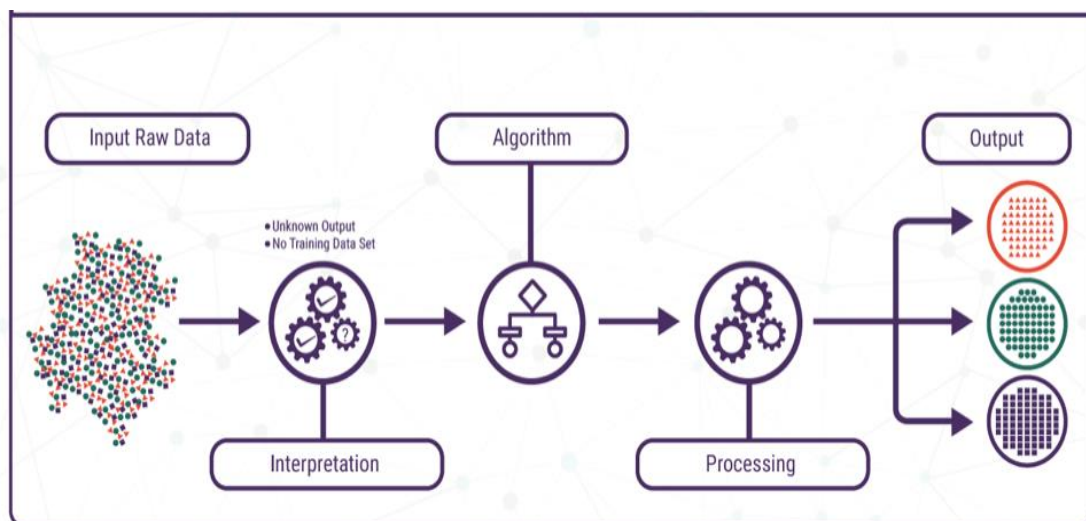


Figure II.11: Unsupervised Learning[20]

2.1.2.1. Types of unsupervised Machine learning Algorithms

A. Clustering

Clustering is the most popular technique in unsupervised learning where the task of partitioning the dataset into groups, called clusters. The goal is to split up the data in such a way that points within a single cluster are very similar and points in different clusters are different. Similarly, to classification algorithms, clustering algorithms assign (or predict) a number to each data point, indicating which cluster a particular point belongs to [2].

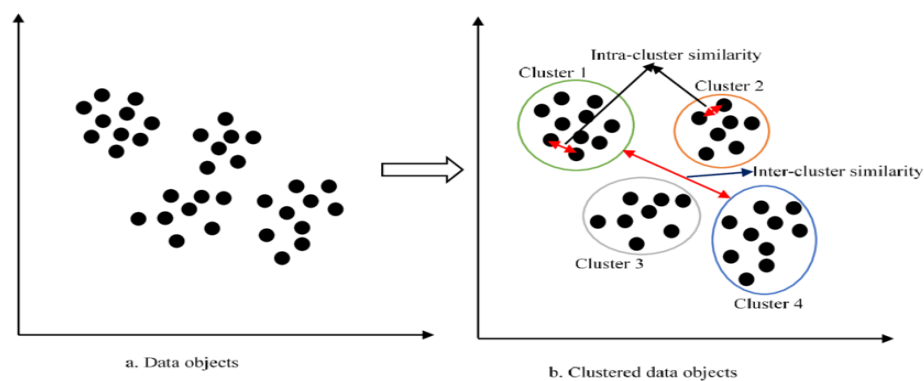


Figure II.12: Clustering Algorithms[21]

▪ Dimensionality Reduction

Dimensionality reduction is a method of analyzing high-dimensional data by reducing the number of covariates by deleting indeterminate characteristics or consolidating several features into single elements, making the data more interpretable. Dimensional reduction has advantages in that it removes associated aspects in the data and allows for easier visualization, such as in two dimensions, but combined features can become less interpretable and some information will definitely be lost. The most basic dimensional reduction approaches are unsupervised algorithms that operate on the entire dataset by maintaining the most dominant features or by discovering new features [5].

2.1.2.2. Common unsupervised Learning Algorithms

A. K-Means Clustering

K-means clustering is one of the simplest and most commonly used clustering algorithms. It searches for cluster centers that are representative of specific data regions. The algorithm alternates between two steps: assigning each data point to the cluster center that is

closest to it, and then setting each cluster center as the mean of the data points assigned to it. When the assignment of instances to clusters no longer changes, the algorithm is complete [2].

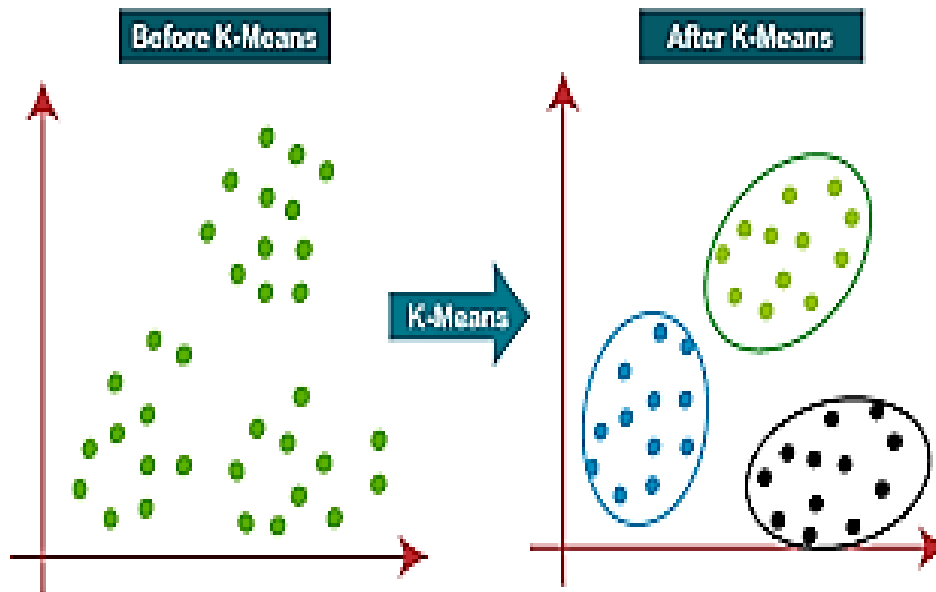


Figure II.13: K-Means clustering[22]

B. Principal component analysis (PCA)

Principal component analysis (PCA) is a method for rotating a dataset so that the rotated features are statistically uncorrelated. This rotation is frequently followed by the selection of only a subset of the new features, based on their importance in explaining the data [2].

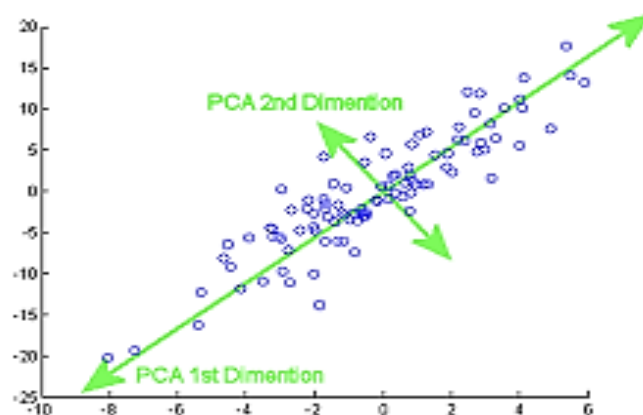


Figure II.14: Principal component analysis[23]

3. Deep learning

Deep Learning (DL), also known as deep structured learning or hierarchical learning, is a branch of Machine Learning (ML) that employs a set of algorithms to model high-level abstractions in data. Such algorithms develop a layered, hierarchical architecture of learning and representing data. This hierarchical learning architecture is inspired by artificial intelligence emulating the deep, layered learning process of the primary sensorial areas of the neocortex in human brain, which automatically extracts features and abstractions from underlying data. Based on DL algorithms are useful when it comes to dealing with large amounts of unsupervised data and naturally learn data representations in a greedy layer-wise method[26].

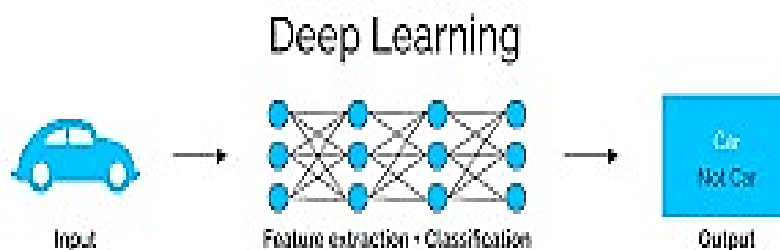


Figure II.15: Deep learning[24]

4. Artificial Neural Networks

4.1. The biological neuron

A typical biological neuron is composed of a cell body, a tubular axon, and a multitude of hair-like dendrites; Dendrites form a fine filamentary brush that surrounds the neuron's body. The axon is a long, thin tube that splits into branches and ends in small end bulbs that brush up against the dendrites of neighboring cells. A synapse is a tiny space between an end bulb and a dendrite through which information is sent. A single neuron's axon creates synaptic connections with a large number of other neurons; the presynaptic side of the synapse refers to the neuron that sends the signal, while the postsynaptic side refers to the neuron that receives the signal [7].

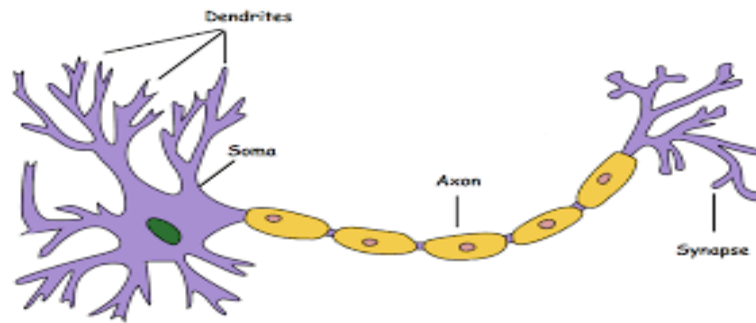


Figure II.16: Biological neuron[25]

4.2. The Perceptron model

The perceptron is binary classifiers with a simple input–output relationship, in which we sum number of inputs times their associated weights and then transmit this "net input" to a step function with a given threshold. This is often a Heaviside step function with a threshold value of 0.5 in perceptrons. Depending on the input, this function will return a single real-valued binary value (0 or 1) [7].

4.3. Component of artificial neural network

4.3.1. Input layer

It takes in the input data for the neural network. It doesn't apply any computations on the input values and simply passes on the values to the next layer.

4.3.1. Hidden layers

This is the middle layer of neural network, this is also known as the black box. All the nodes of input layer is connected to the nodes of hidden layers. Every hidden layers are associated with the activation function.

4.3.2. Output layers:

This is the last layer of the neural network which is responsible for prediction. Each nodes of hidden layers is connected with the output layer and the output generated by hidden layers are transferred to the output layer for the evaluation purpose. The output layer is also associated with the activation function which gives the probability of the levels.

4.3.3. Weight

This is something which model learns while training. When the input passed to the neural networks based on the importance model used to assign the value to that input and that value is nothing it's a weight at very high level.

4.3.4. Biases

Which are constant, are an additional input into the next layer that will always have the value of 1. Bias units are not influenced by the previous layer (they do not have any incoming connections) but they do have outgoing connections with their own weights. The bias unit guarantees that even when all the inputs are zeros there will still be an activation in the neuron.

4.3.5. Activation Functions

The activation function helps to determine the output of Neural Network. They decide whether the neuron should be activated or not. It determines the output of a model, its accuracy, and computational efficiency. Inputs are fed into the neurons in the input layer. Inputs (X_i) are then multiplied with their weights (W_i) and add the bias gives the output ($y = (X_i * W_i) + b$) of the neuron. We apply our activation function on Y then it is transfer to the next layer.

A. Sigmoid function (Logistic function)

This function takes any real value as input and outputs values in the range 0 to 1. The larger the input (more positive), the closer the output value will be to 1, whereas the smaller the input (more negative), the closer the output will be to 0.

$$f(x) = \frac{1}{1+e^{-x}} \quad (\text{II.1})$$

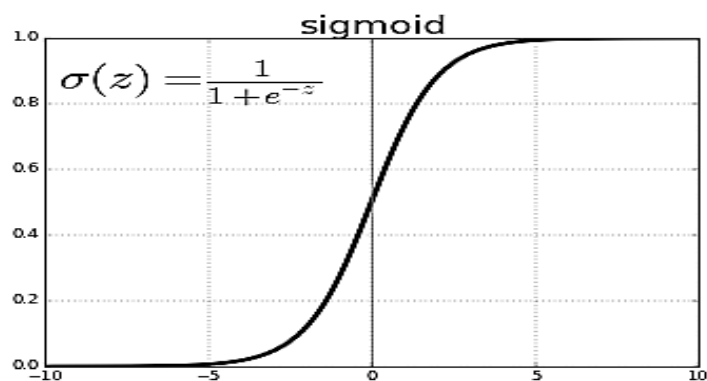


Figure II.17: Sigmoid function[26]

B. Tanh function

This function is very similar to the sigmoid activation function and even has the same S-shape. It takes any real value as input and outputs values in the range -1 to 1. The larger the input (more positive), the closer the output value will be to 1, whereas the smaller the input (more negative), the closer the output will be to -1.

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (\text{II.2})$$

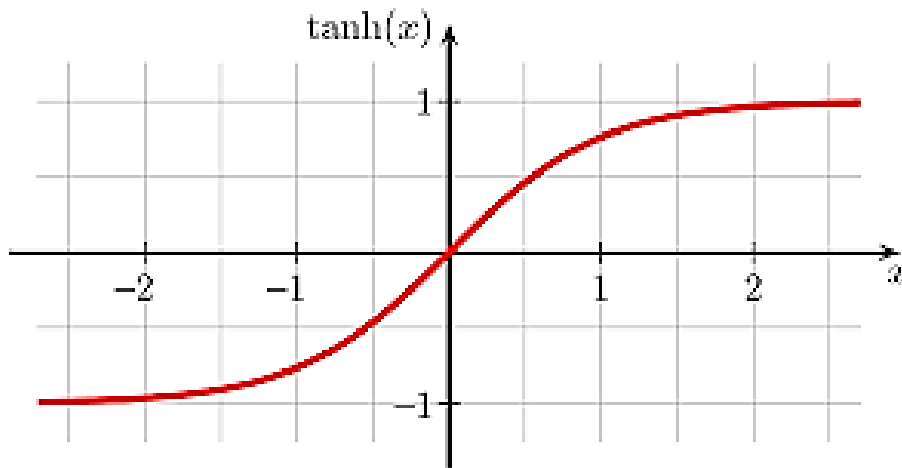


Figure II.18: Tanhfunction[27]

C. ReLU function

The ReLU is the most used activation function in the world right now. Since, it is used in almost all the convolutional neural networks or deep learning. It gives an output of x if x is positive and 0 otherwise.

$$f(x) = \max(0, x) \quad (\text{II.3})$$

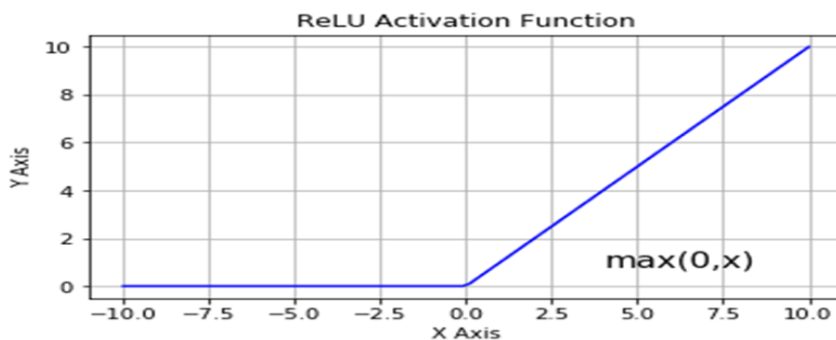


Figure II.19: ReLufunction[28]

D. Softmaxfunction

The softmax activation function is the generalized form of the sigmoid function for multiple dimensions. It is the mathematical function that converts the vector of numbers into the vector of the probabilities.

$$f(x) = \frac{e^{x_i}}{\sum_j e^{x_j}} \quad (\text{II.4})$$

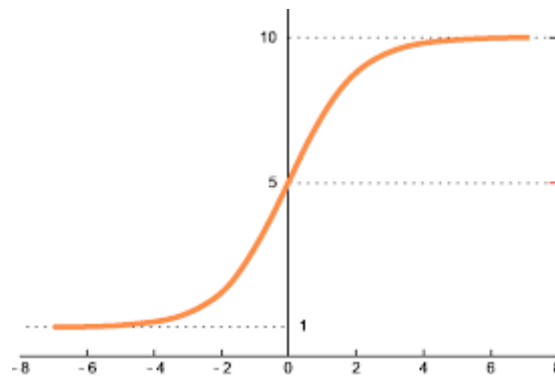


Figure II.20: Softmaxfunction[29]

4.3.6. Cost function

A cost function is a measure of error between what value your model predicts and what the value actually is. For example, represent the prediction or output of some arbitrary model for the point x_i with parameters θ .

$$\sum_{i=1}^n (y_i - f_{\theta}(x_i))^2 \quad (\text{II.5})$$

Where y_j is the actual value and x_i is the predict value.

4.3.7. Hyperparameters

Hyperparameters are tuning parameters that help networks train better and faster, and they have an influence on optimization functions and model selection during the training of our learning algorithm, because updates are equivalent to the steps the algorithm takes throughout the weight space to reduce error.

Hyperparameter selection ensures that the model does not underfit or overfit the training dataset and that it learns the data structure as rapidly as feasible. [7].

A. Learning Rate

The learning rate influences how much you adjust parameters during optimization to reduce the error of neural network guesses. It is a coefficient that scales the size of the steps (updates) a neural network takes to its parameter vector x as it crosses the loss function space [7].

A. Regularization

Regularization helps with the effects of out-of-control parameters by using different methods to minimize parameter size over time.

Regularization coefficients L1 and L2 help fight overfitting by making certain weights smaller. Smaller-valued weights lead to simpler hypotheses, and simpler hypotheses are the most generalizable. Unregularized weights with several higher-order polynomials in the feature set tend to overfit the training set [7].

B. Momentum

Momentum helps the learning algorithm get out of spots in the search space where it would otherwise become stuck. In the errorscape, it helps the updater find the gulleys that lead toward the minima [7].

4.3.8. Optimizers

Optimizers are algorithms or methods used to change the attributes of your neural network such as weights and learning rate in order to reduce the losses.

A. Gradient descent

The gradient descent algorithm calculates the weights and bias variations for each observation but performs the learning (weights and bias update) only after all observations have been evaluated[8].

B. Stochastic gradient descent

The Stochastic gradient descent (abbreviated SGD) method estimates the cost function's gradient and then adjusts the weights and biases for each observation in the dataset [8].

$$\theta = \theta - \eta \cdot \nabla_{\theta} J(\theta; x^{(i)}; y^{(i)}) \quad (\text{II.6})$$

where θ is a parameter (theta), e.g. your weights, biases and activations. η is the learning rate (eta), but also sometimes alpha α or gamma γ is used. ∇ is the gradient (nabla), which is taken of J . J is formally known as objective function, but most often it's called cost function or loss function.

C. Adam

The last algorithm we will look at is called Adam (Adaptive Moment estimation). , it uses an exponential weighted averages of past derivatives; it uses the exponentially weighted averages of past squared derivatives [8].

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (\text{II.7})$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (\text{II.8})$$

Where m and v are moving averages, g is gradient on current mini-batch, and betas — new introduced hyper-parameters of the algorithm. They have default values of 0.9 and 0.999 respectively.

D. RMSprop

The RMSprop optimizer restricts the oscillations in the vertical direction. Therefore, we can increase learning rate and algorithm could take larger steps in the horizontal direction converging faster.

$$E[g^2]_t = \beta E[g^2]_{t-1} + (1 - \beta) \frac{\delta C}{\delta w} \quad (\text{II.9})$$

$$W_t = W_{t-1} - \frac{\eta}{\sqrt{E[g^2]_t}} \frac{\delta C}{\delta w} \quad (\text{II.10})$$

Where $E[g^2]$ moving average of squared gradients. $\frac{\delta C}{\delta w}$ gradient of the cost function with respect to the weight. η learning rate. β moving average parameter (default value 0.9).

4.3.9. ANN Models

4.3.9.1. Single Layer Perceptron Model (SLP)

The single layer perceptron (SLP) model is the simplest form of neural network and the basis for the more advanced models that have been developed in deep learning. Typically, we use SLP in classification problems where we need to give the data observations labels (binary or multinomial) based on inputs. The values in the input layer are directly sent to the output

layer after they are multiplied by weights and a bias is added to the cumulative sum. This cumulative sum is then put into an activation function, which is simply a function that defines the output. When that output is above or below a user-determined threshold, the final output is determined [6].

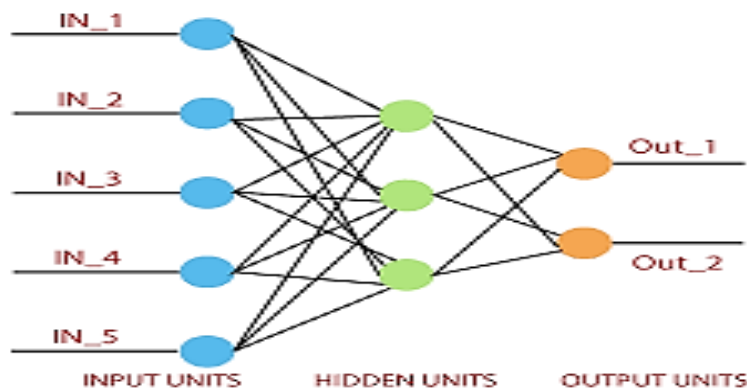


Figure II.21: Single layer perceptron network[30]

4.3.9.2. Multilayer Perceptron Model (MLP)

Very similar to SLP, the multilayer perceptron (MLP) model features multiple layers that are interconnected in such a way that they form a feed-forward neural network. Each neuron in one layer has directed connections to the neurons of a separate layer. One of the key distinguishing factors in this model and the single layer perceptron model is the back-propagation algorithm, a common method of training neural networks [6].

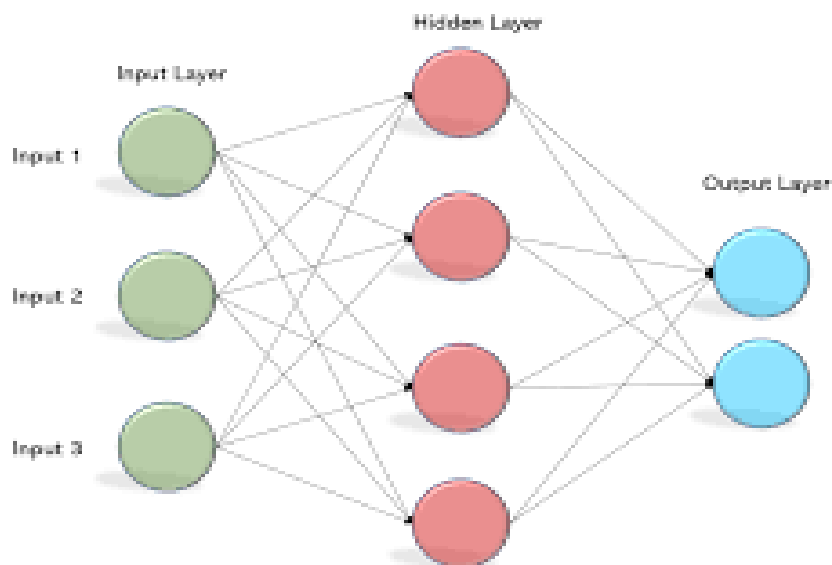


Figure II.22: Multilayers perceptron network[31]

4.3.10. Type of ANN

4.3.10.1. Recurrent Neural Networks (RNNs)

Recurrent neural networks (RNNs) are models of artificial neural networks (ANNs) where the connections between units form a directed cycle. Specifically, a directed cycle is a sequence where the walk along the vertices and edges is completely determined by the set of edges used and therefore has some semblance of a specific order. RNNs are often specifically used for speech and handwriting recognition [6].

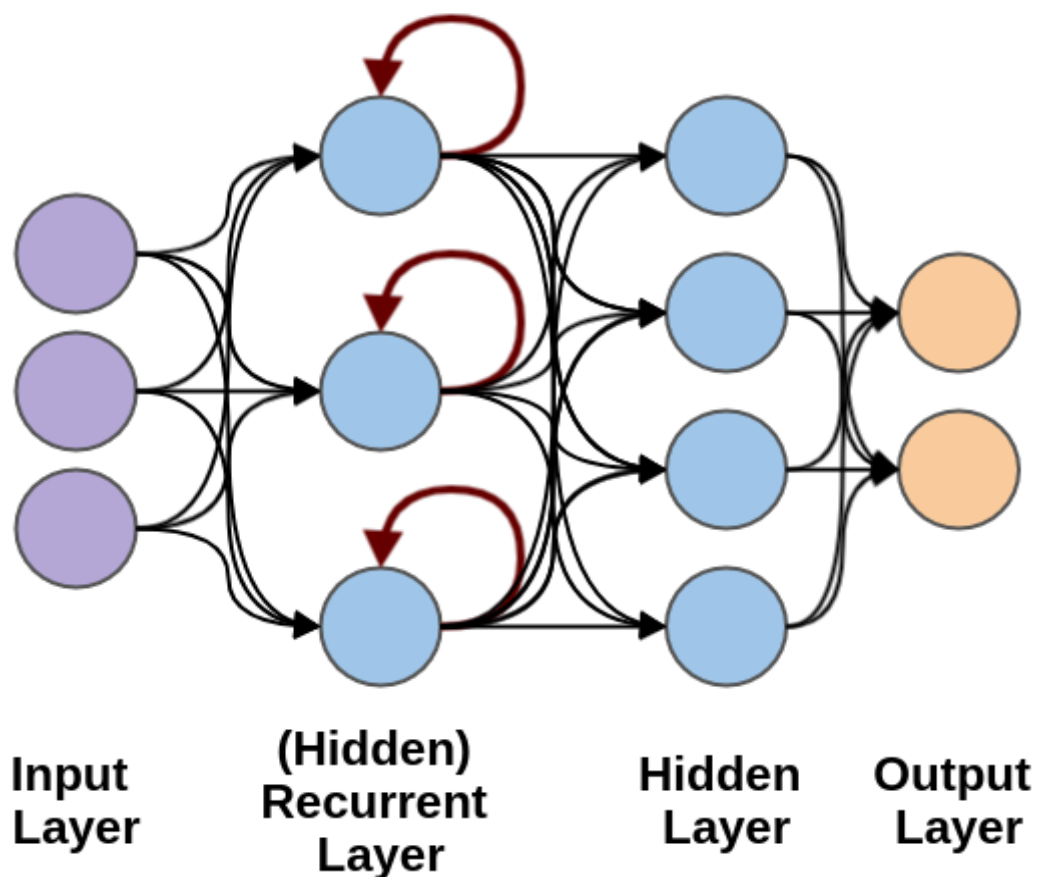


Figure II.23: Recurrent neural network[32]

4.3.10.2. Convolution Neural Network (CNNs)

A Convolutional Neural Network is a Deep Learning algorithm, which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive

methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics [9].

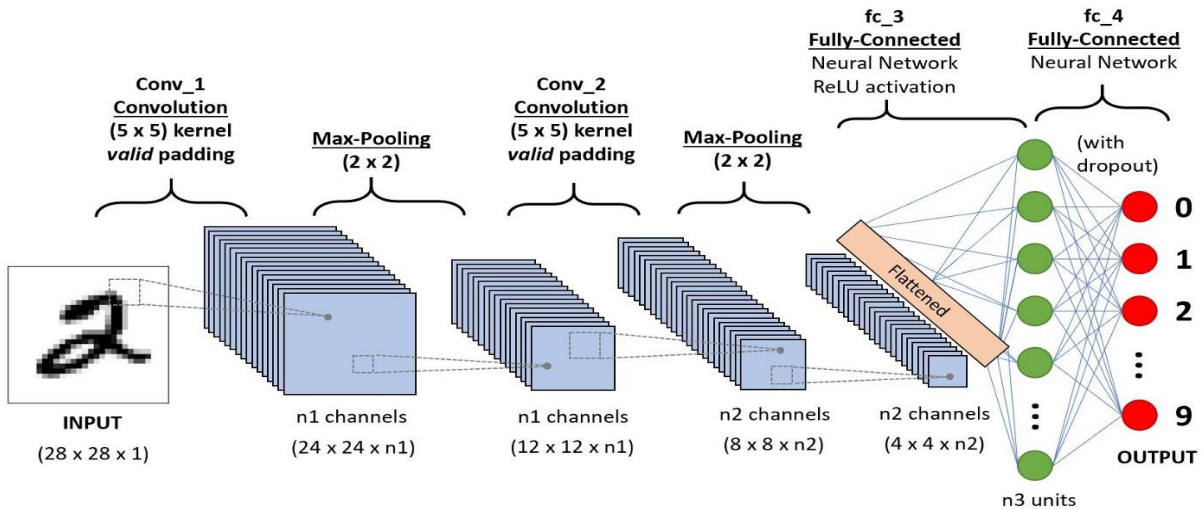


Figure II.24: Convolution Neural Network[33]

4.3.10.2.1. Types of layers in a convolutional network

A. Convolution layer

A convolution layer is a fundamental component of the CNN architecture that performs feature extraction, which typically consists of a combination of linear and nonlinear operations, convolution operation and activation function [10].

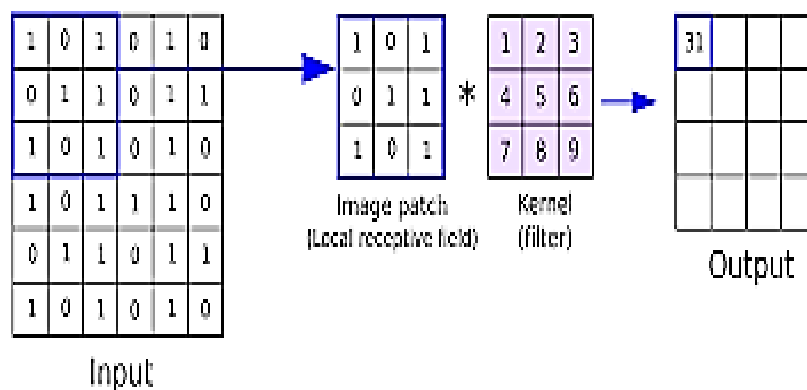


Figure II.25: Convolution layer[34]

B. Pooling layer

A pooling layer provides a typical down sampling operation, which reduces the in-plane dimensionality of the feature maps in order to introduce a translation invariance to small shifts and distortions, and decrease the number of subsequent learnable parameters. It is of note that there is no learnable parameter in any of the pooling layers, whereas filter size, stride, and padding are hyperparameters in pooling operations, similar to convolution operations [10].

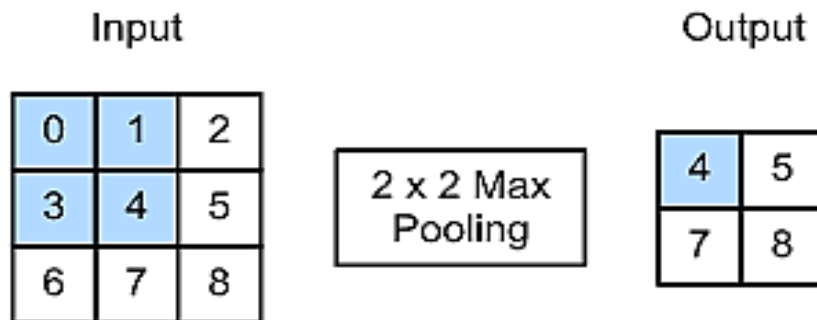


Figure II.26: Max pooling[35]

C. Fully connected layer

The output feature maps of the final convolution or pooling layer is typically flattened, transformed into a one-dimensional (1D) array of numbers (or vector), and connected to one or more fully connected layers, also known as dense layers, in which every input is connected to every output by a learnable weight. Once the features extracted by the convolution layers and down sampled by the pooling layers are created, they are mapped by a subset of fully connected layers to the final outputs of the network, such as the probabilities for each class in classification tasks. The final fully connected layer typically has the same number of output nodes as the number of classes. Each fully connected layer is followed by a nonlinear function, such as ReLU[10].

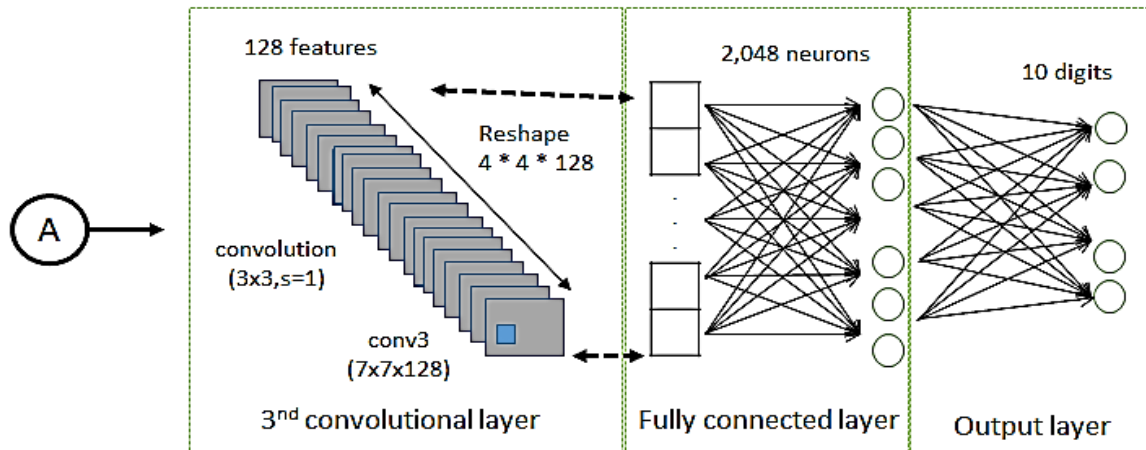


Figure II.27: Fully connected layer[36]

4.3.10.2.2. Convolutional Neural Network Models

Lenet

Lenet was originally proposed in 1990s by LeCun in 1998. The main objective of his work was to build better pattern recognition system, which provided a way of automatic learning rather hand-designed heuristics. It gets popularity in 2010 with availability of sufficient computational infrastructure and more memory capacity. It is a seven level convolutional network with the backpropagation algorithm. The LeNet-5 architecture consists with seven layers: two convolutional layers, two subsampling layers, then two fully connected layers and lastly a softmax classifier layer. All these layers contains trainable parameters called weights. The total number of weights obtained in LeNet is 431k [11].

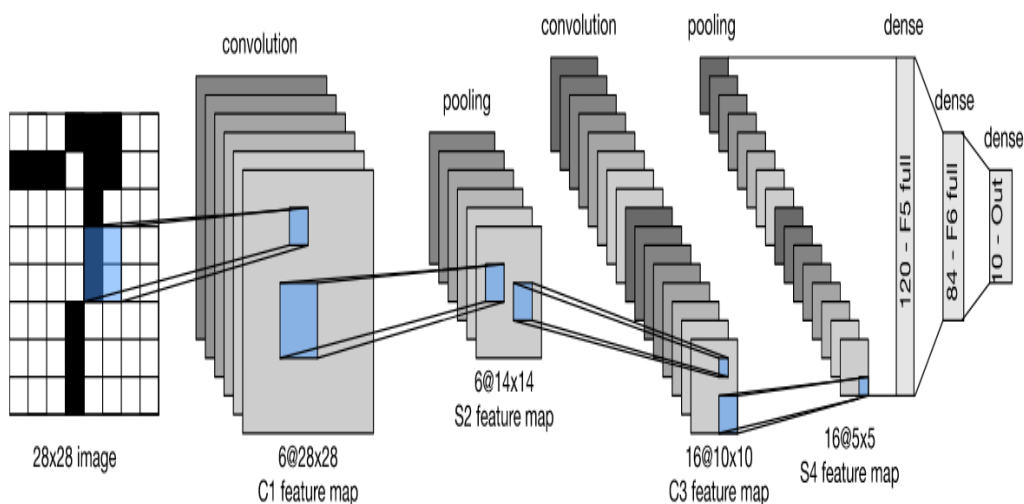


Figure II.28: LeNetarchitecture[37]

AlexNet

AlexNet proposed by Alex Krizhevsky and others in 2012. It comprised with more profound and more extensive CNN architecture as compare to LeNet [13]. As compare to an existed machine learning and image processing methods, AlexNet came up with high rate of recognition accuracy. As after the introduction of AlexNet, the field of deep learning expanded quickly, it is considered as major breakthrough in many fields that includes image classification and visual recognition. There are five convolutional layers are available in AlexNet. In addition, it comprises with three fully connected layers [11].

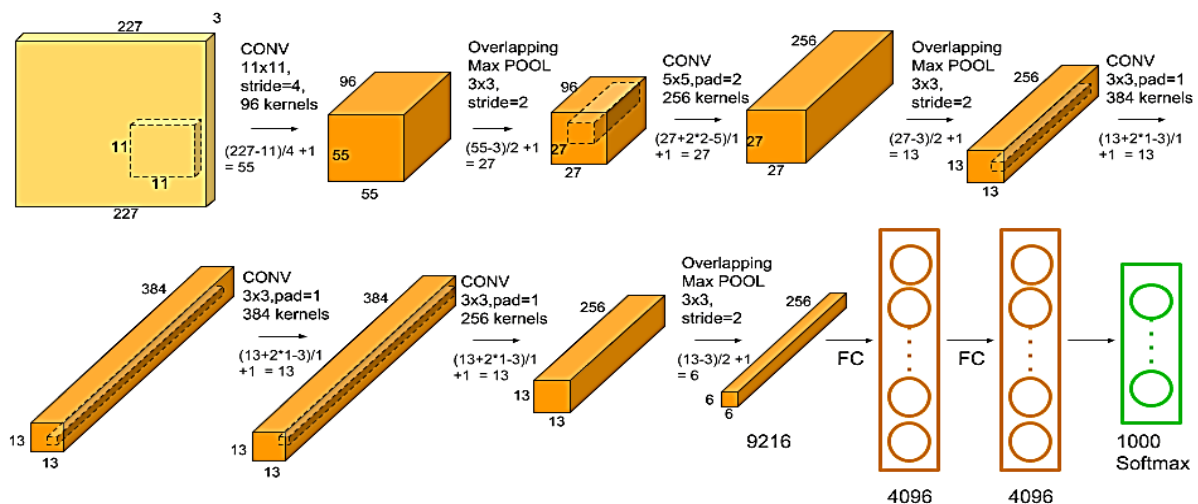


Figure II.29: AlexNet architecture [38]

VGGNet

VGGNet was developed by Simonyan and Zisserman. VGGNet used 3x3 filters. To achieve the accuracy of classification and recognition tasks, depth of a network plays an important role and therefore, it is a critical component of VGGNet. The VGG architecture comprises of two convolutional layers. Both of these layers utilized ReLU for activation. A Soft-max layer for classification is the last layer of the architecture. The weight configuration of the VGGNet is openly available and used by many other applications. However, 138 million parameters of VGGNet are bit challenging to handle, but it worked well on both image classification and localization tasks [11].

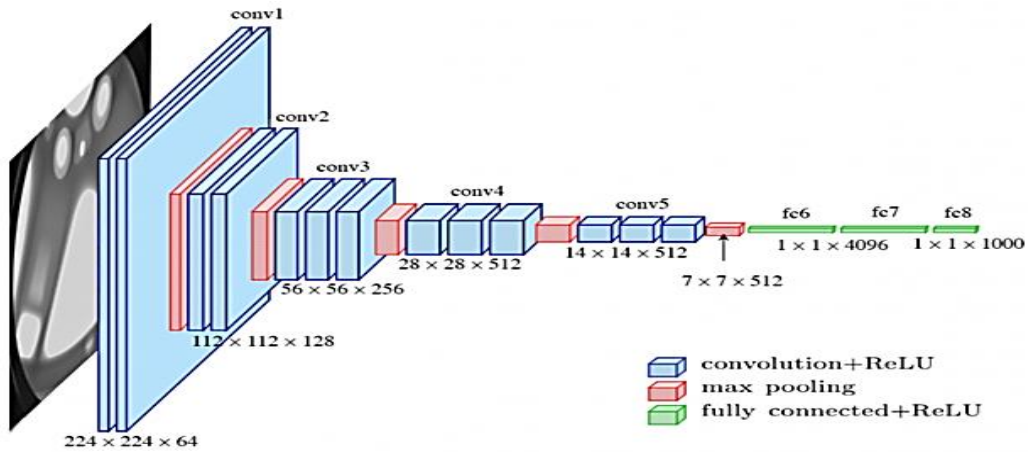


Figure II.30: VGGNetarchitecture[39]

ResNet

ResNet is an entirely deep network, developed by Kaiming He, it resolved the problem of vanishing gradient , sets new standards, provides state-of-the-art performance for classification, detection, and localization tasks. It provides a way to train a Neural Network with 152 layers. It has a popular variant called ResNet50 that has total fifty layers including forty nine convolution layers and one fully connected layer at the end of the network [11].

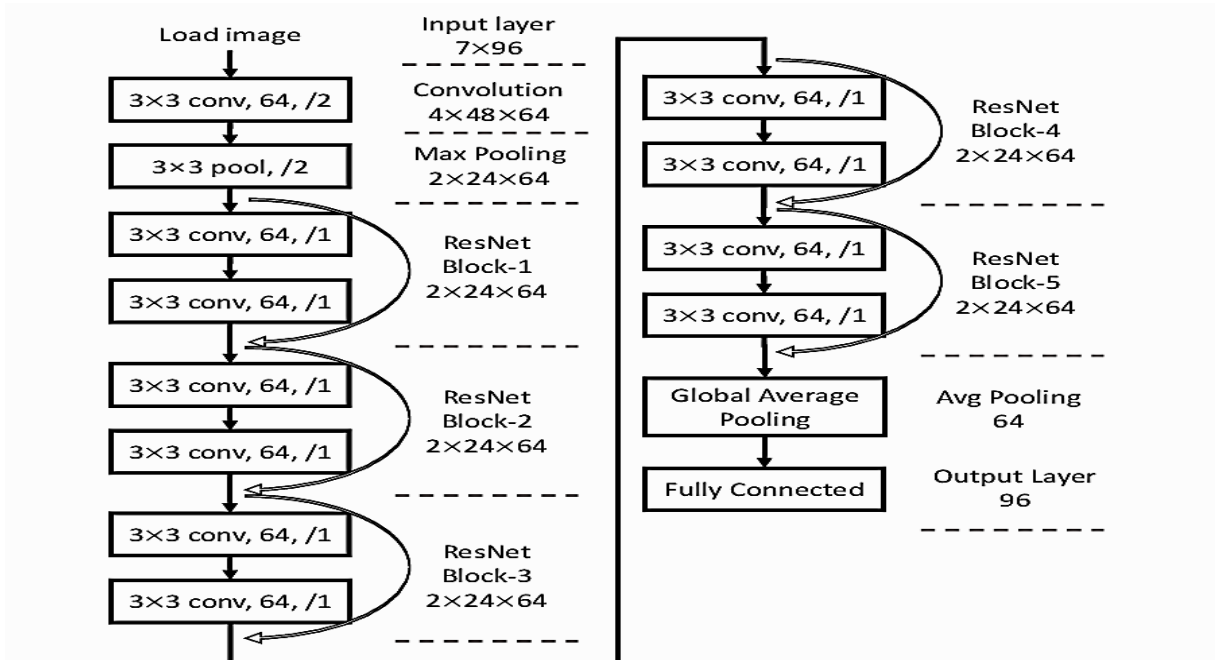


Figure II.31: ResNetarchitecture[40]

Inception

Inception is an extended network of the popular GoogLeNet which has achieved good classification performance in several biomedical applications using transfer learning. Following GoogLeNet, Inception proposed a model which concatenates multiple different sized convolutional filters into a new filter. Such design decreases the number of parameters to be trained and thereby reduces the computational complexity [27].

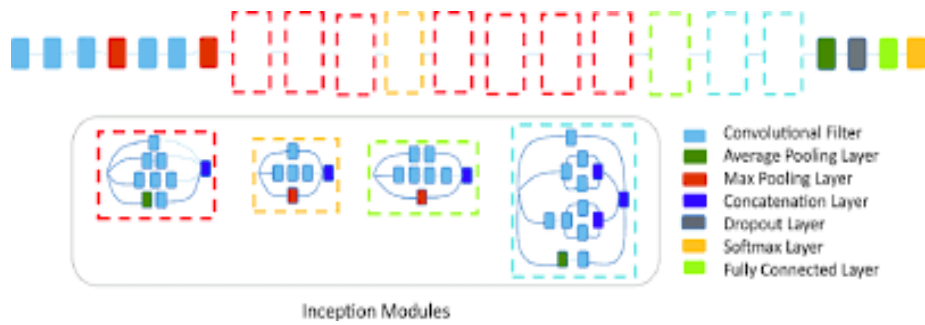


Figure II.32: Inception –v3 architecture [46]

4.3.10.2.3. Transfer Learning

Transfer learning is a technique whereby a model is trained and developed for one task and is then re-used on a second related task. It refers to the situation whereby what has been learnt in one setting is exploited to improve optimization in another setting. Transfer Learning is usually applied when there is a new dataset smaller than the original dataset used to train the pre-trained model.

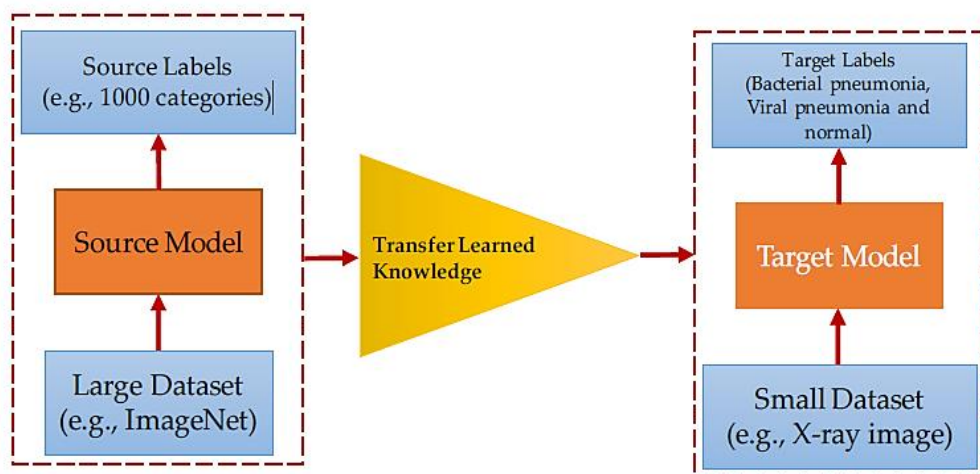


Figure II.33: Transfer Learning [41]

Conclusion

We have devoted this chapter to the presentation of basic notions such as AI, machine learning and its types and we conclude with deep learning where we have shown an overview of the perceptron and his type with how it works.

Chapter III State of Art

Introduction

The accurate classification of banknote fitness when sorting paper currency is an important and challenging task. To address this task a group of researchers suggested several methods.

Related work

TuyenDanh Pham, Dat Tien Nguyen, Wan Kim, Sung Ho Park and Kang Ryoung Park papers

These researchers have so far suggested three studies to solve this problem.

First study

In 2015, They proposed a classifications method for fit and unfit banknotes using denominations of 10, 20, 50, 100 and 500 Rupees. The input banknotes were captured by visible light image sensors, then the classification is conducted based on the features extracted from the regions of interest (ROIs), which contain little texture. And discrete wavelet transformation (DWT) is used to extract the features for discriminating between fit and unfit banknotes, the optimal DWT features are selected based on linear regression analysis with ground-truth data measured by densitometer. The selected features are used as the inputs to a support vector machine (SVM) for the final classification of banknote fitness [15].

Second study

In 2016, They proposed a new fitness classifications method for all denominations of the United States Dollar (USD) and the Korean Won (KRW) banknotes, they used the regions of interest (ROIs) for extracting features from the visible light reflection (VR) images and near-infrared light transmission (NIRT) images were set differently according to banknote denomination and direction; from these ROI, the average values of the VR and NIRT images were extracted as features. They applied fuzzy system to the features acquired from input images to determine the final fitness values for the input images and determine whether the relevant banknotes were usable based on two classes (Fit, Unfit)[16].

Third study

In 2018, they proposed a deep learning classification method using convolution neural network on the gray-scale banknote images captured by visible-light one-dimensional line image sensor. Their proposed model designed to classify the fitness of banknote into two or three levels including fit, normal and unfit for recirculation, depending on banknotes from three national currencies, which are INR, KRW, and USD. The CNN architecture used for experiments in this study consists of five convolutional layers, denoted as C1 to C5, followed by three fully connected layers, denoted as F1 to F3. For faster training time with gradient descent, rectified linear unit (ReLU) layers are presented at all of the convolutional layers and fully connected layers of the network. Following each CNN layer in the first, second and fifth convolutional layer is the max pooling layer [17].

Comparison of the proposed methods

Method	Advantages	Disadvantages
Method 1	Less resource requirement owing to the small sizes of processing areas and features.	Defects and damages can occur on the non-selected regions of the banknote.
Method 2		
Method 3	Pre-classification of banknote's denomination and input direction is not required.	Intensive training of the CNN is required.

Table III.1: Comparison of the proposed methods

To capture banknote images, a commercial banknote counting machine was used in this study.

Banknote counting machine

Cash counting machines are made to count the number or denomination of bills that are placed into the machine. They pull in the bills, count the amount that was inserted, and give you the correct number of bills in a stack. This saves a lot of time and offers a mistake-free way to count large sums.



Figure III.1: Banknote counting machine[42]

Nancy Chinyere Woods and Halimah Shadiat Oladosu paper

In this work, they proposed a system to recognize naira banknotes and also determine the notes fitness for use in an ATM. They used only the ₦1,000 and the ₦500 notes which were scanned and labelled as ATM fit or ATM unfit based on the Central Bank of Nigeria (CBN) banknote fitness guidelines. For every naira note image in the dataset, Speeded-Up Robust Features (SURF) was used to extract several key points of varying sizes and orientation and these were stored for reference. Given a test image, K-nearest neighbour (KNN) algorithm was used to match its features with pre-computed features to determine the note's denomination. The test note's fitness was then determined by calculating the image quality difference between the test note and a similar reference note using mean square error (MSE), peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) [28].

Weizhong Sun Yue Ma, Zhenyu Yin and Ai Gu

They proposed a new fitness classifications method for denominations of 100 Renminbi based on convolutional neural network for how banknotes accurately identify the soiling of banknotes. The contact image sensor is used to collect the double-sided reflection images of banknotes under red light, green light, blue light and infrared light[29].

Nishant Behar and Manish Shrivastava Paper

They proposed an effective convolutional neural network based (CNN-based) model that exploits the transfer-learning technique for automatic image classification between malignant and benign tumour, using histopathology images. Resnet50 architecture has been trained on new dataset for feature extraction, and fully connected layers have been fine-tuned

for achieving highest training, validation and test accuracies .Their study results present in Figure III.2[30].

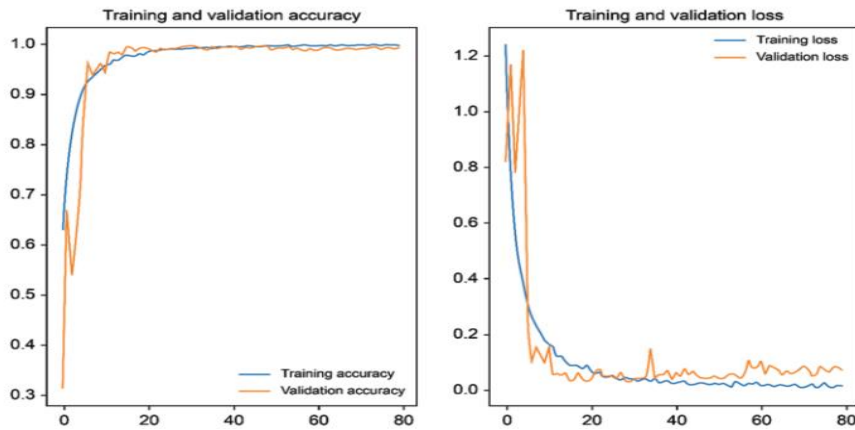


Figure III.2: Training and testing accuracy and loss of ResNet50[49]

Muhammad Mujahid ,FurqanRustam , Roberto Álvarez, Juan Luis Vidal Mazón , Isabel de la Torre Díez , and Imran Ashraf paper

They proposed an automatic pneumonia detection approach using chest X-ray images with deep learning-based ensemble models. Reduced training time and higher accuracy are obtained by leveraging the pre-trained models and combining them with a custom-built CNN model. The Inception-V3 ensemble achieved the highest accuracy among the models, respectively. The ResNet50 ensemble, followed by the VGG-16 ensemble .Their study results present in Figure III.3[31].

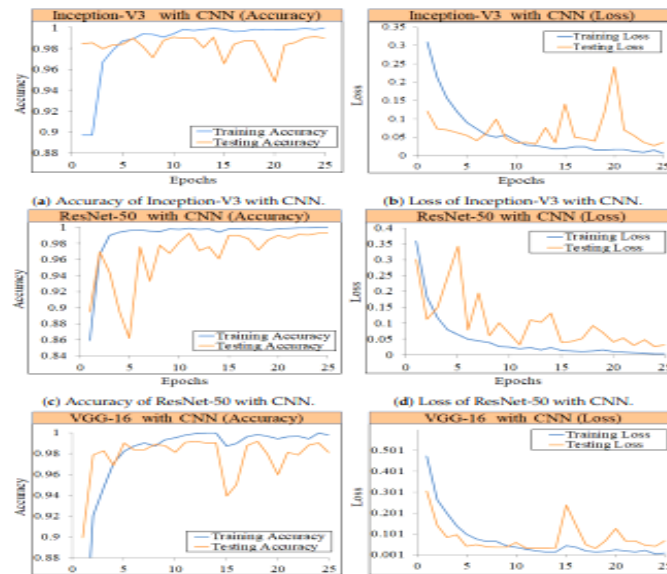


Figure III.3: Training and testing accuracy and loss of ensemble models(Inception-V3,ResNet-50 and VVG-16)[49]

Conclusion:

There are many researches on the fitness classification of banknotes. In this chapter, we have taken an overview of these researches.

Chapter IV Experiments and realization

Introduction

This chapter is devoted to the present the tools and libraries used in our experiments, the realization and the implementation of system and a discussion about the results.

2. Tools and Libraries

1.1. Python

Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together. Python is simple, easy to learn syntax emphasizes readability and therefore reduces the cost of program maintenance. Python supports modules and packages, which encourages program modularity and code reuse. The Python interpreter and the extensive standard library are available in source or binary form without charge for all major platforms, and can be freely distributed [19].



Figure IV.1 : The logo of python[43]

1.2. TensorFlow

TensorFlow is an open-source end-to-end platform for creating Machine Learning applications. It is a symbolic math library that uses dataflow and differentiable programming to perform various tasks focused on training and inference of deep neural networks. It allows developers to create machine learning applications using various tools, libraries, and community resources.

Currently, the most famous deep learning library in the world is Google's TensorFlow. Google product uses machine learning in all of its products to improve the search engine, translation, image captioning or recommendations [20].



Figure IV.2: The logo of TensorFlow [44]

1.3. Anaconda

Anaconda is an open-source distribution of the Python and R programming languages for data science that aims to simplify package management and deployment. Package versions in Anaconda are managed by the package management system, conda, which analyzes the current environment before executing an installation to avoid disrupting other frameworks and packages [21].

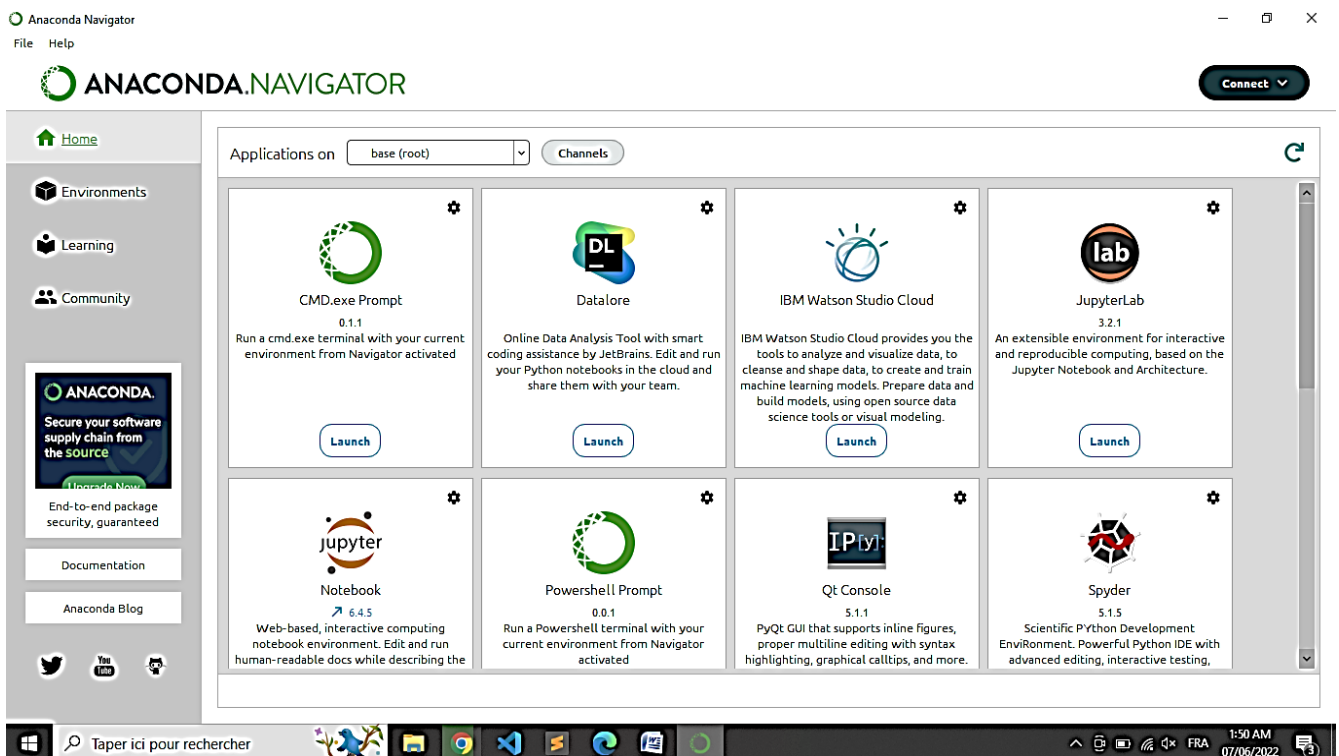


Figure IV.3: The interface of Anaconda

1.4. Jupyter notebook

Jupyter is a free, open-source, interactive web tool known as a computational notebook, which researchers can use to combine software code, computational output, explanatory text and multimedia resources in a single document. Computational notebooks have been around for decades, but Jupyter in particular has exploded in popularity over the past couple of years. This rapid uptake has been aided by an enthusiastic community of user-developers and a redesigned architecture that allows the notebook to speak dozens of programming languages a fact reflected in its name, which was inspired, according to co-founder Fernando Pérez, by the programming languages Julia (Ju), Python (Py) and R[22].

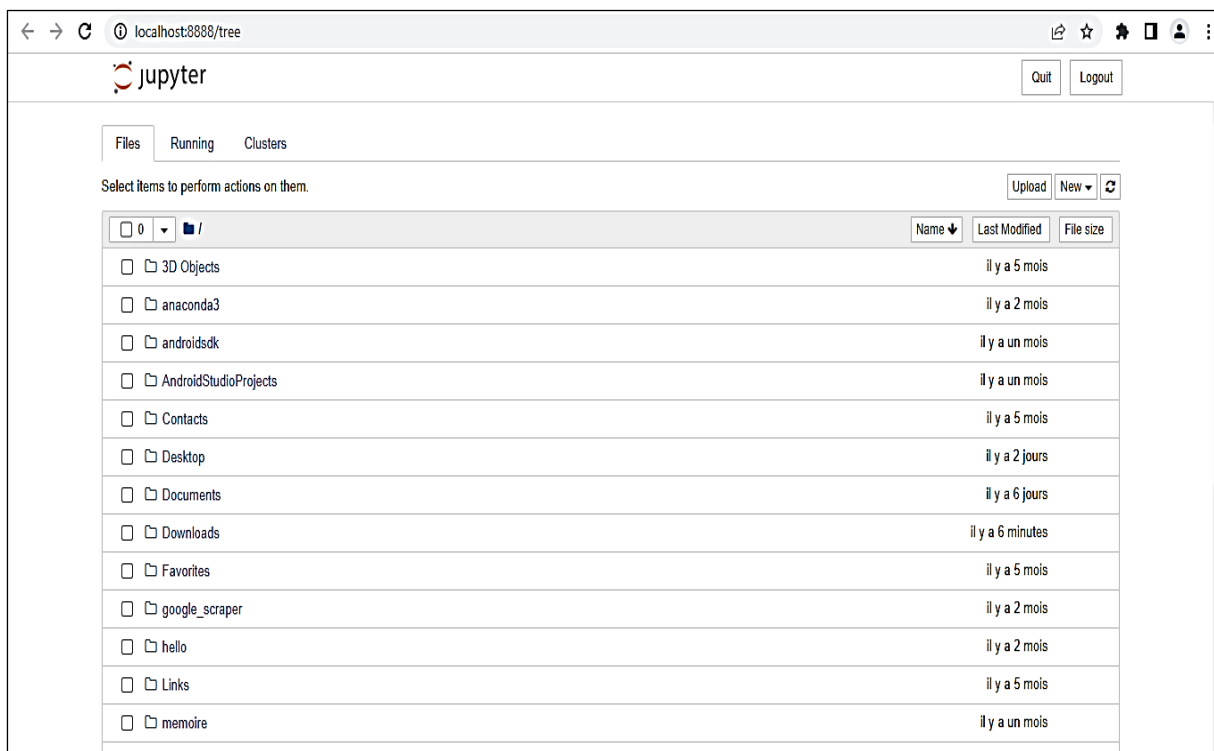


Figure IV.4: The interface of Jupyter notebook

1.5. Google Colab

Google Colab was developed by Google to provide free access to GPU's and TPU's to anyone who needs them to build a machine learning or deep learning model. Google Colab can be defined as an improved version of Jupyter Notebook [23].

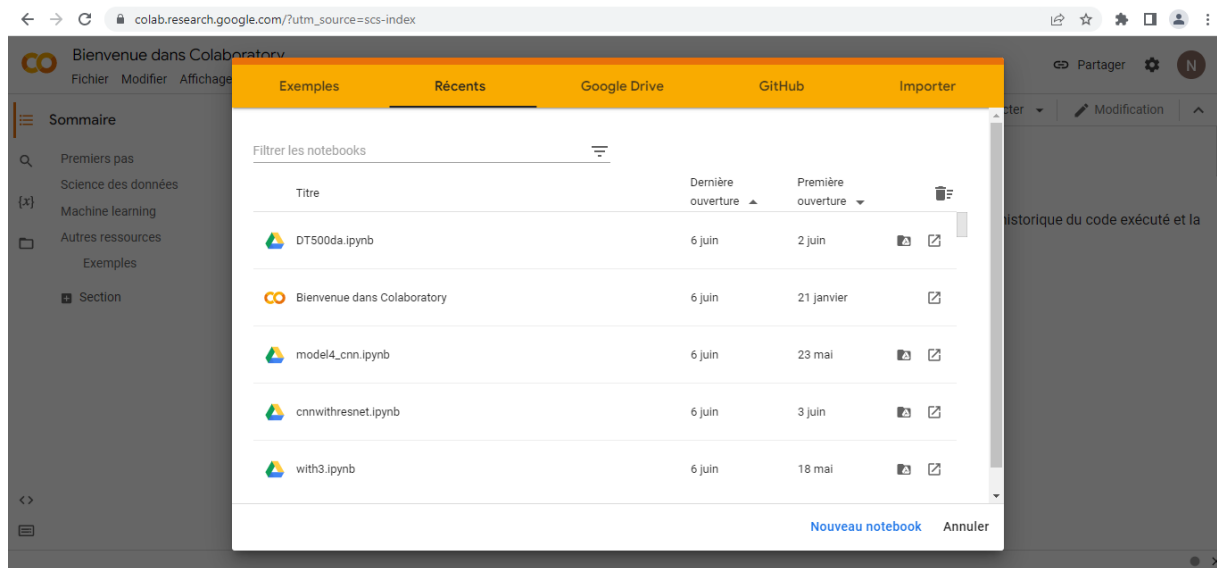


Figure IV.5: The interface of Google Colab

1.6. Keras

Keras is a high-level, deep learning API developed by Google for implementing neural networks. It is written in Python and is used to make the implementation of neural networks easy. It also supports multiple backend neural network computation. Keras is relatively easy to learn and work with because it provides a python frontend with a high level of abstraction while having the option of multiple back-ends for computation purposes. This makes Keras slower than other deep learning frameworks, but extremely beginner-friendly[24].



Figure IV.6: The logo of Keras[45]

1.7. Flask

Flask is a web application framework written in Python. It was developed by Armin Ronacher, who led a team of international Python enthusiasts called Pocco. Flask is based on the Werkzeug WSGI toolkit and the Jinja2 template engine. Both are Pocco projects [25].



Figure IV.7: The logo of Flask[46]

2. Experiments

In this research, we tried to train the network models for our banknote dataset. We performed data augmentation for expanding the number of images for training. This process helps to generalize the training data and reduce overfitting.

The results were always mediocre so we decided to use already existing models with denser convolutional architectures and which are usually trained on massive datasets, it can be used directly in making predictions on new tasks or integrated into the process of training a new model. and it has already proven acceptable performance in the field of automatic classification.

2.1. Our datasets

We have collected a banknote fitness dataset of Algerian currencies, with denominations of 500, and we divided it into 2 classes of banknote (Fit and Unfit), containing 582, 480 for train and 102 for validation according to some standards that we obtained from a bank employee and one of the professors at the Higher School of Banks for unfit banknote, which are:

- Part of the banknote is missing, provided that it does not exceed half of it.
- Banknotes soiled with dirt, fats, colors and oils.
- Banknotes that contain adhesive tape.
- Burnt banknotes.
- Two-part banknotes with different numbers.
- Worn banknotes.
- Banknotes that contain many writings, drawings and seals, which leads to the obliteration of its features.



Figure IV.8: Example of fit banknote



Figure IV.9: Example of unfit Banknote

2.2. Architecture of our network

2.2.1. Model 1

The CNN architecture used in our proposed method is shown in Figure IV.10. This network structure consists of six convolutional layers, denoted as C1 to C9. For faster training time with gradient descent, rectified linear unit (ReLU) layers are presented at all of the convolutional layers. Following each CNN layer we use Batchnormalization, max pooling and drop out layer layers. The banknote images in our proposed method are resized equally to 300*300 pixels, the resulting banknote feature map after five convolutional layers has the size of $6 \times 2 \times 128$.

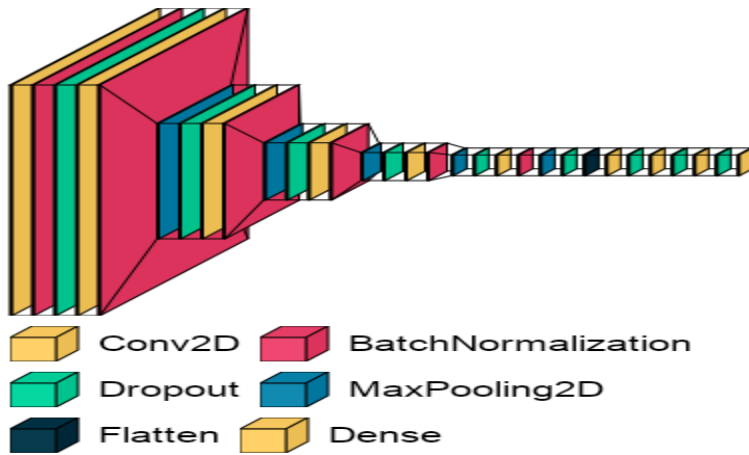


Figure IV.10: Architecture of our proposed model

After six layers of convolution, we use a neural network composed of four layers fully connected and three of dropout of 50% as shown in figure IV.14. The first layer have 20148 neurons where the activation function used is the ReLU with , the second layer have 256 neurons with same activation function ,the third layer have 8 neurons with also same activation function , and the last layer is a sigmoid which allows to calculate the distribution of probability of 1 classes .

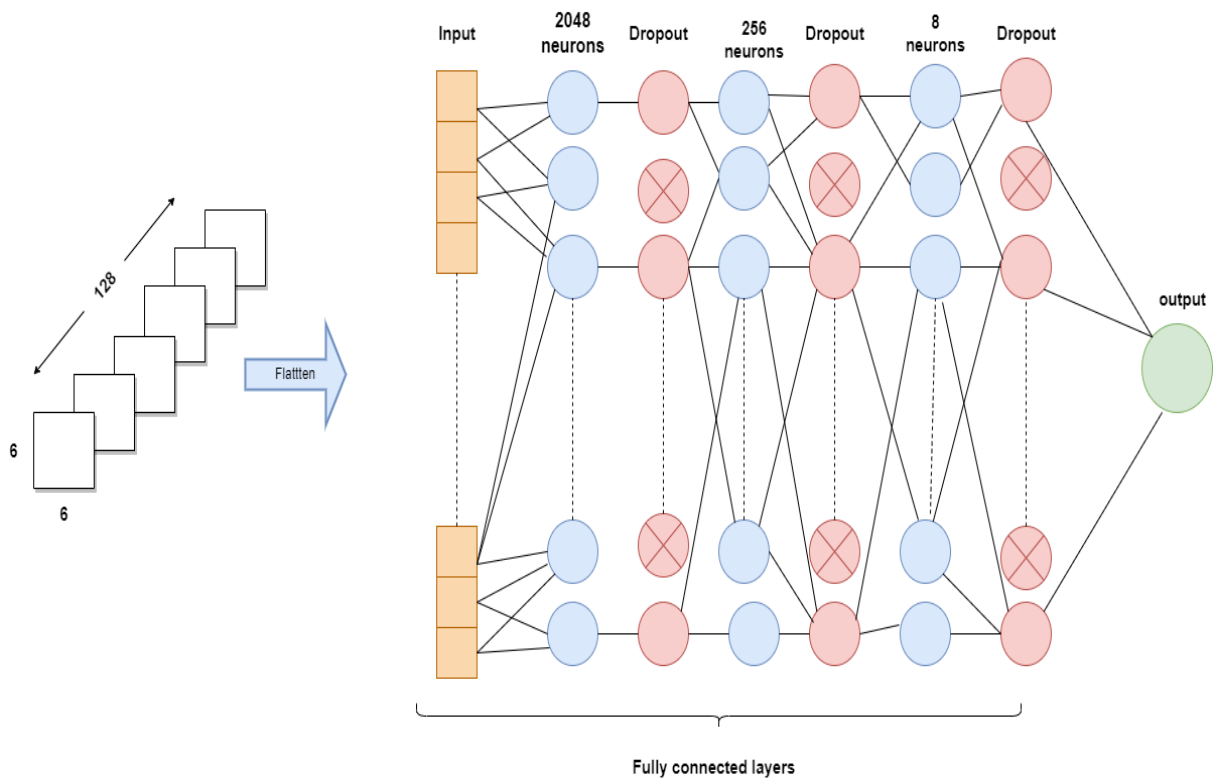


Figure IV.11: The Fully connected layers used in model1

2.2.2. Model 2

In the second model we used Resnet50 model, which present in figure IV.12, we use the input size as $224 \times 224 \times 3$. It performs the initial convolution, max-pooling using 7×7 , and 3×3 kernel sizes respectively. Afterward, Stage 1 of the network starts and it has 3 Residual blocks containing 3 layers each. The size of kernels used to perform the convolution operation in all 3 layers of the block of stage 1 are 64, 64 and 128 respectively. Bottleneck design is used, for each residual function F, 3 layers are stacked one over the other. The three layers are 1×1 , 3×3 , 1×1 convolutions. The 1×1 convolution layers are responsible for reducing and then restoring the dimensions. The 3×3 layer is left as a bottleneck with smaller input/output dimensions, Then we have an Average Pooling layer .

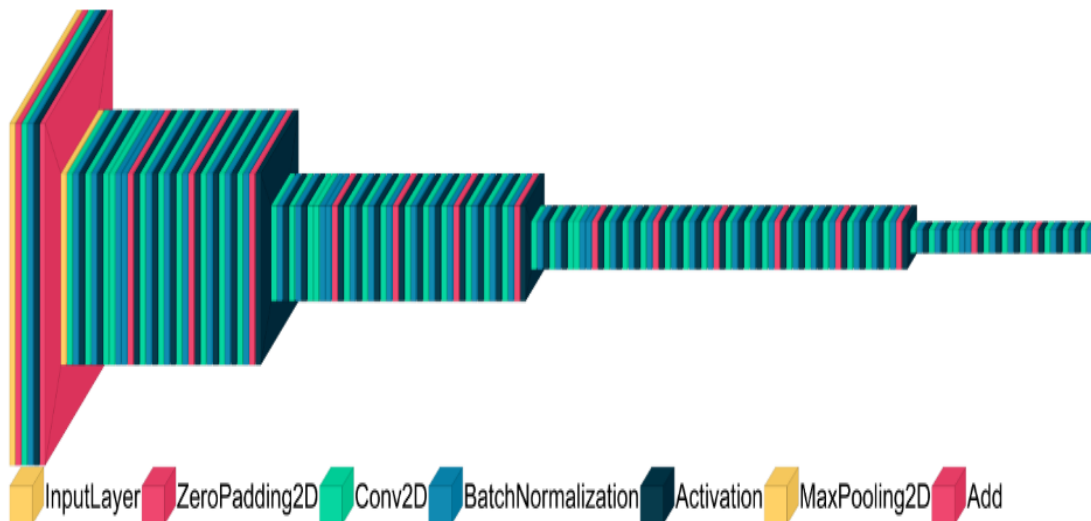


Figure IV.12: Architecture of Resnet50

In the last, we added a neural network composed of three layers fully connected and two layers of drop out. The first one has 1024 neurons and the second one has 128 where the activation function that is used is the ReLU following by Dropout layer of 50% in both. Finally we'll flatten the output of the CNN layers, feed it into the last layer, and then to a sigmoid layer for binary classification.

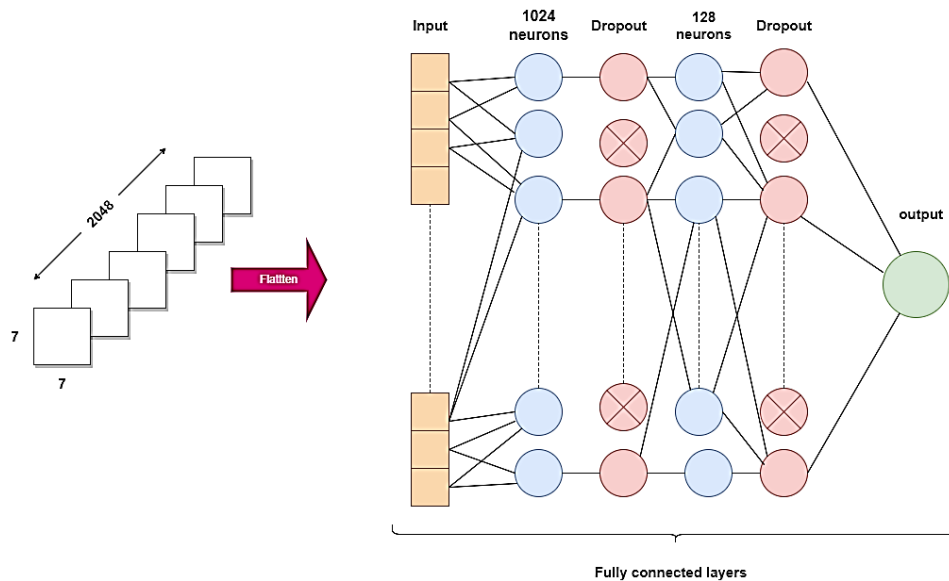


Figure IV.13: The Fully connected layers used in model2

2.2.3. Model 3

In the third model, we used Inception-v3, which is present in figure IV.14. There are three kinds of Inception modules in Inception-v3, Inception A, Inception B and Inception C. The Inception modules are well-designed convolution modules that can both generate discriminatory features and reduce the number of parameters. It performs convolution on an input, with 3 different sizes of filters (1x1, 3x3, 5x5). Additionally, max pooling and average pooling are also performed. The outputs are concatenated and sent to the next inception module. There are 3 Inception A modules, 5 Inception B modules and 2 Inception C modules are stacked in series. The input image size is 299x299; After the convolutional layers and Inception modules, the feature map dimensions were 5x5 with 2,048 channels.

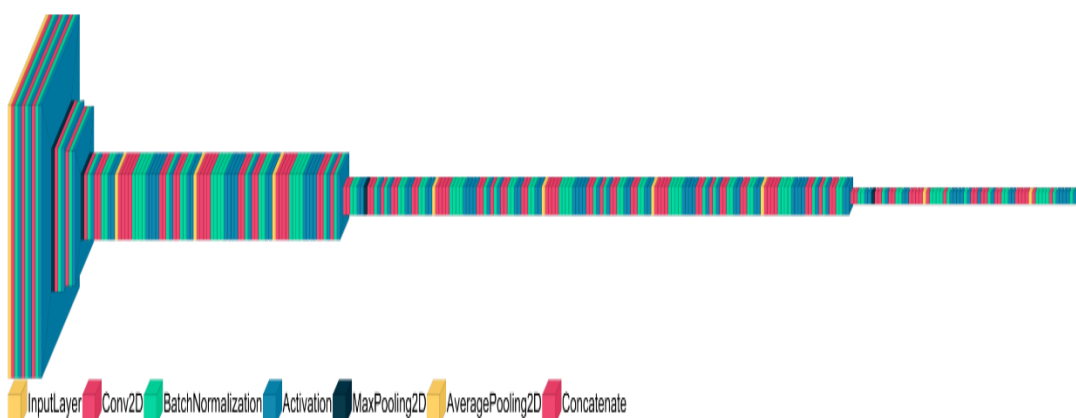


Figure IV.14: Architecture of Inception-v3

In the last, we added a neural network composed of three layers fully connected and two layers of drop out. The first one has 1024 neurons and the second one has 128 where the

activation function that is used is the ReLU following by Dropout layer of 50% in both, Finally we'll flatten the output of the CNN layers, feed it into the last layer, and then to a sigmoid layer for binary classification.

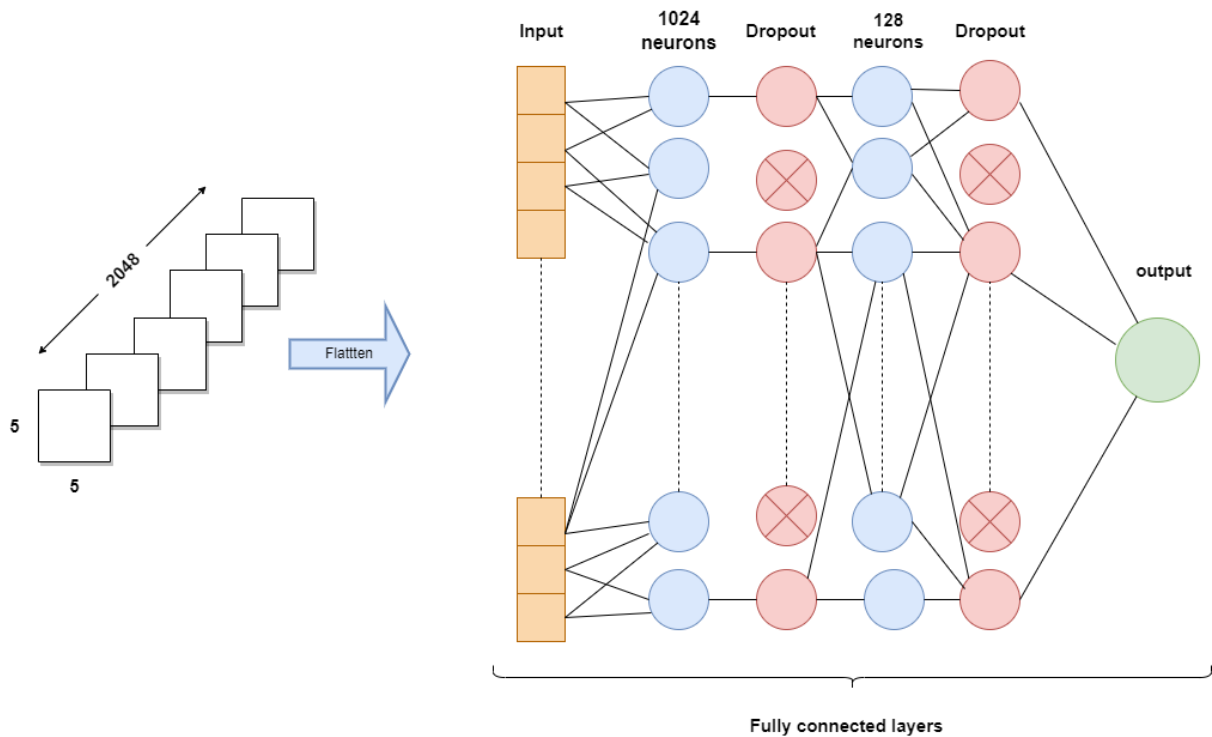
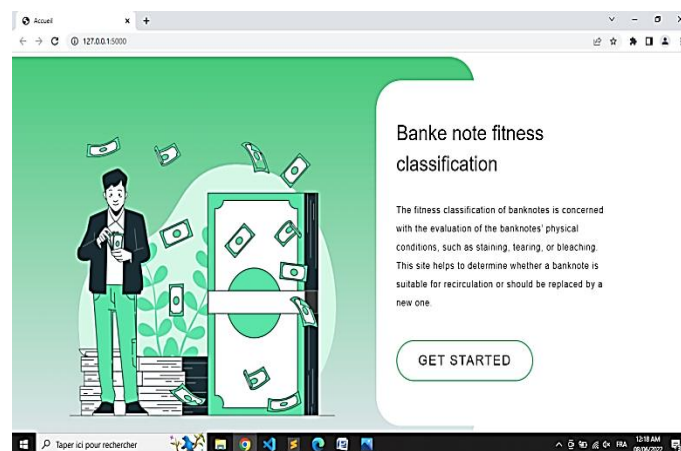


Figure IV.15: The Fully connected layers used in model3

2.3. Implementation

After trained our model and save it we build a webpage using HTML ,CSS , JavaScript then we use flask to serve the saved model with two routes, the first one for index page and the second one for a predict route to make inferences from our saved model



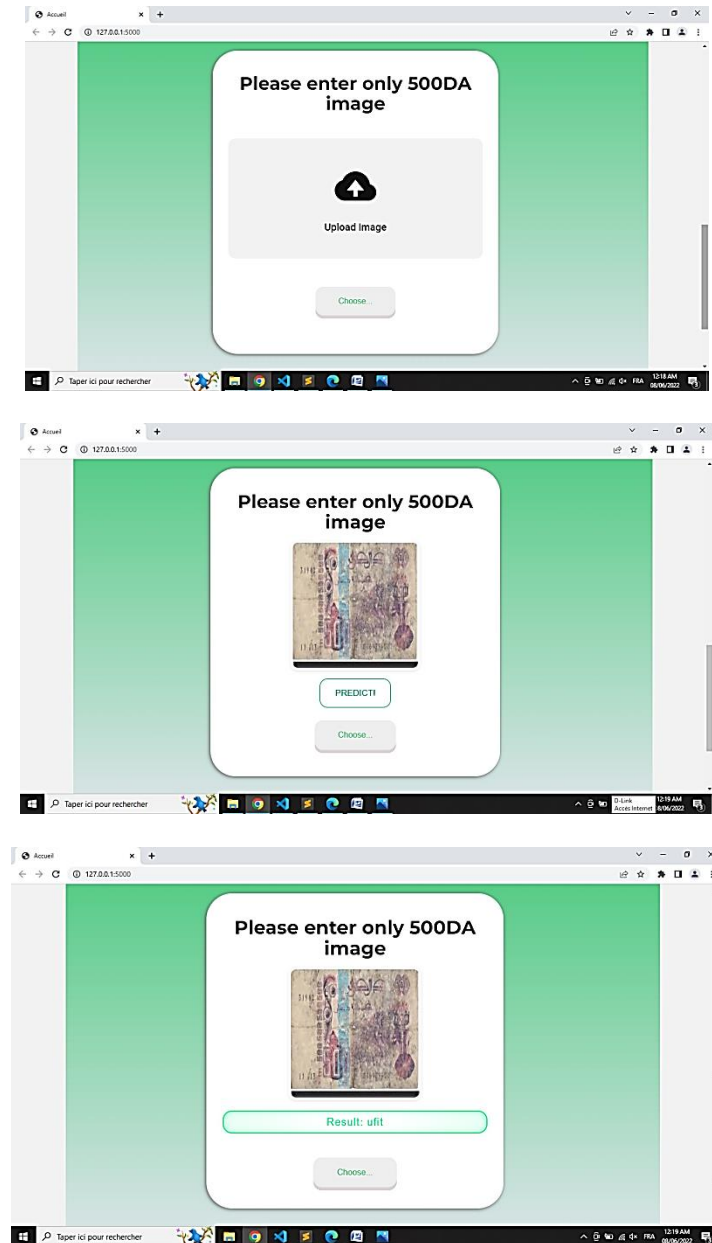


Figure IV.16: Browser user interface

3. Result and discussion

3.2. Results obtained for model 1

After analyzing the results obtained, From figure IV.17, the model is very overfitting because the size of the training dataset used is not enough and very small in addition the quality of images is low. We got an error rate of 55.64% in train and 70.58% in validation, and an accuracy rate of 71.04% in train and 57% in validation when we use Adam optimizer with learning rate equal $1e-6$ and an error rate of 60.77% in train and 67.58% in validation, and an

accuracy rate of 69.58% in train and 60% in validation when we use RMSprop optimizer with learning rate equal $1e-6$ and momentum 0.9.

By comparing the two results(a) and (b), We noticed that (a) is less overfitting than (b).

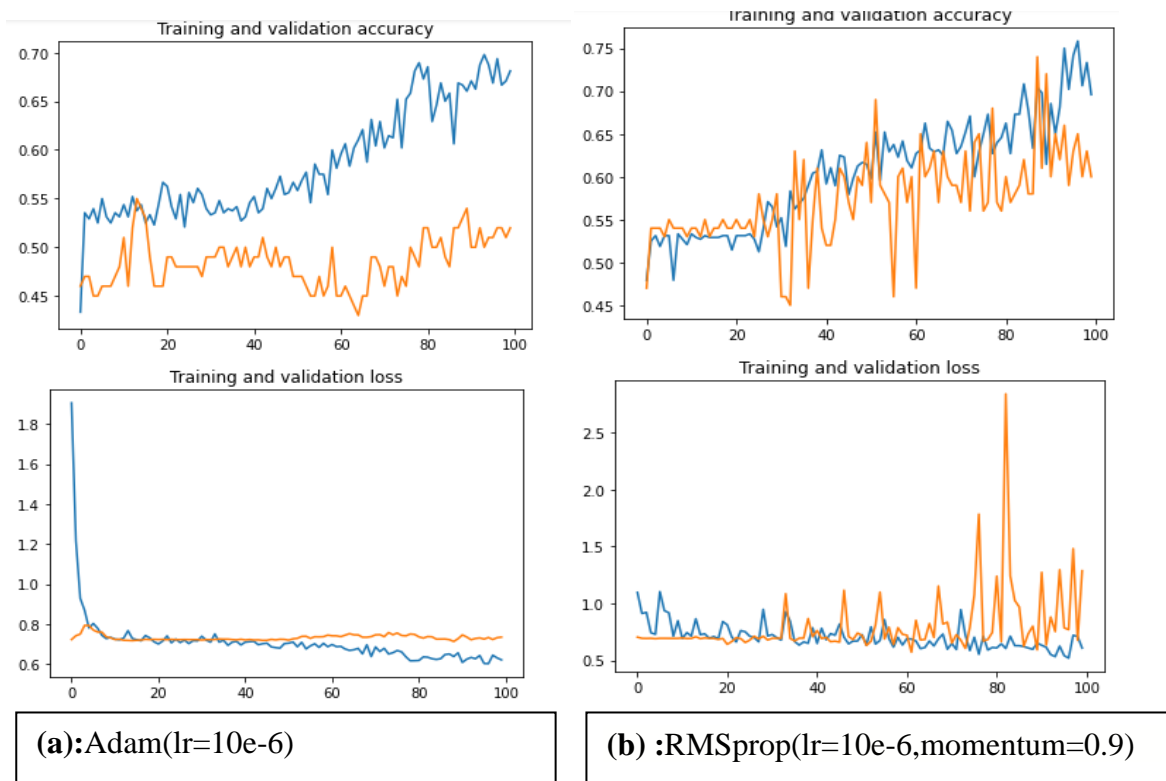


Figure IV.17: Accuracy and loss plots model 1

3.3. Results obtained for model 2

After analyzing the results obtained, the following remarks are noted: From figure IV.18, The accuracy of training and Validation increases with the number of epochs, this reflects that with each epoch the model learns more information. If the accuracy is reduced, then we will need more information to teach our model and therefore we must increase the number of epochs. Likewise, the learning and validation error decreases with the number of epochs. We got an error rate of 22.95% in train and 27.15% in validation, and an accuracy rate of 89.29% in train and 86.27% in validation when we use Adam optimizer with learning rate equal $1e-6$ and an error rate of 30.22% in train and 26.45% in validation, and an accuracy rate of 88.67% in train and 86.05% in validation when we use RMSprop optimizer with learning rate equal $1e-6$ and momentum 0.9. By comparing the two results(a) and (b), We

noticed that There is a small difference between the two results and the result (a) is the best in terms of values of accuracy and loss .

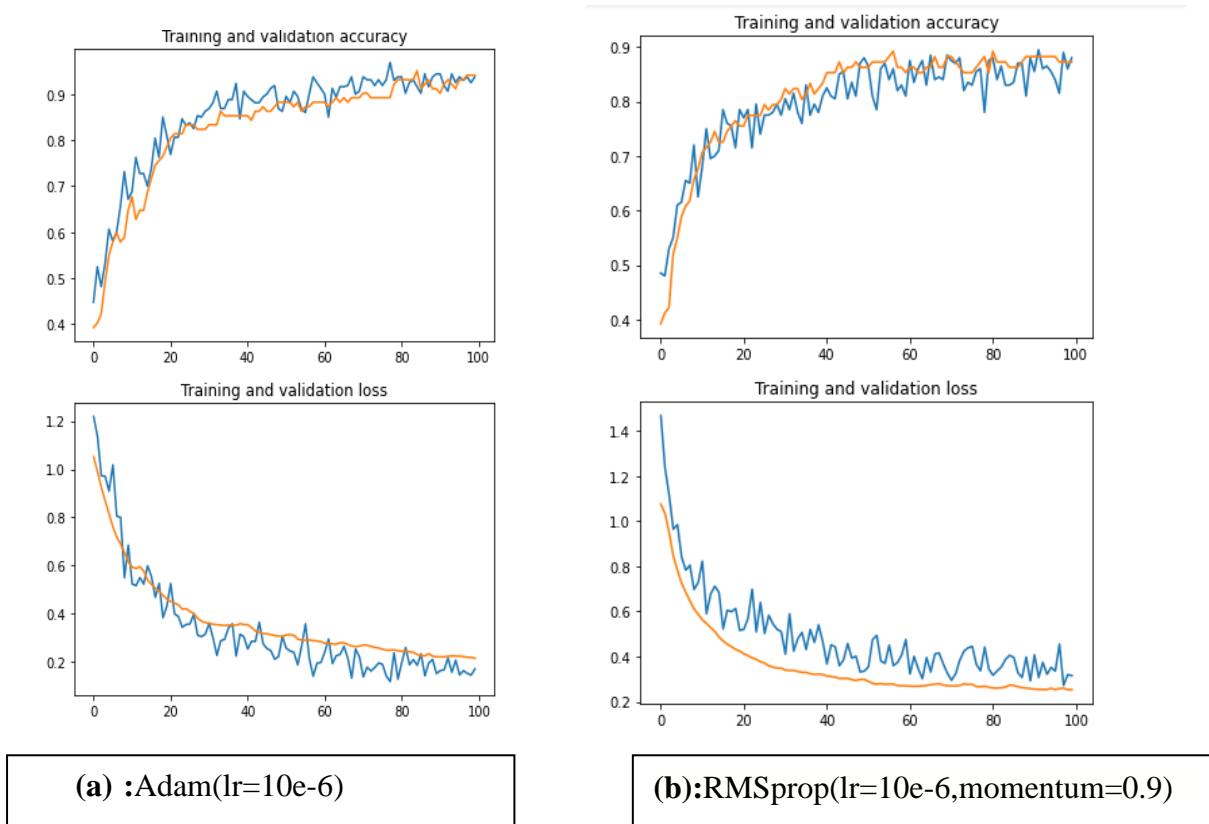


Figure IV.18: Accuracy and loss plots model 2

3.4. Results obtained for model 3

After analyzing the results obtained, the following remarks are noted: From figure IV.19 The accuracy of training and Validation increases with the number of epochs; this reflects that with each epoch the model learns more information. If the accuracy is reduced, then we will need more information to teach our model and therefore we must increase the number of epochs. Likewise, the learning and validation error decreases with the number of epochs. We got an error rate of 35.36% in train and 32.05% in validation, and an accuracy rate of 84.79% in train and 83% in validation when we use Adam optimizer with learning rate equal $1e-6$ and an error rate of 17.68% in train and 16.79% in validation, and an accuracy rate of 95.21% in train and 91% in validation when we use RMSprop optimizer with learning rate equal $1e-6$ and momentum 0.9. By comparing the two results (a) and (b), We noticed that the result (b) is better than (a) .

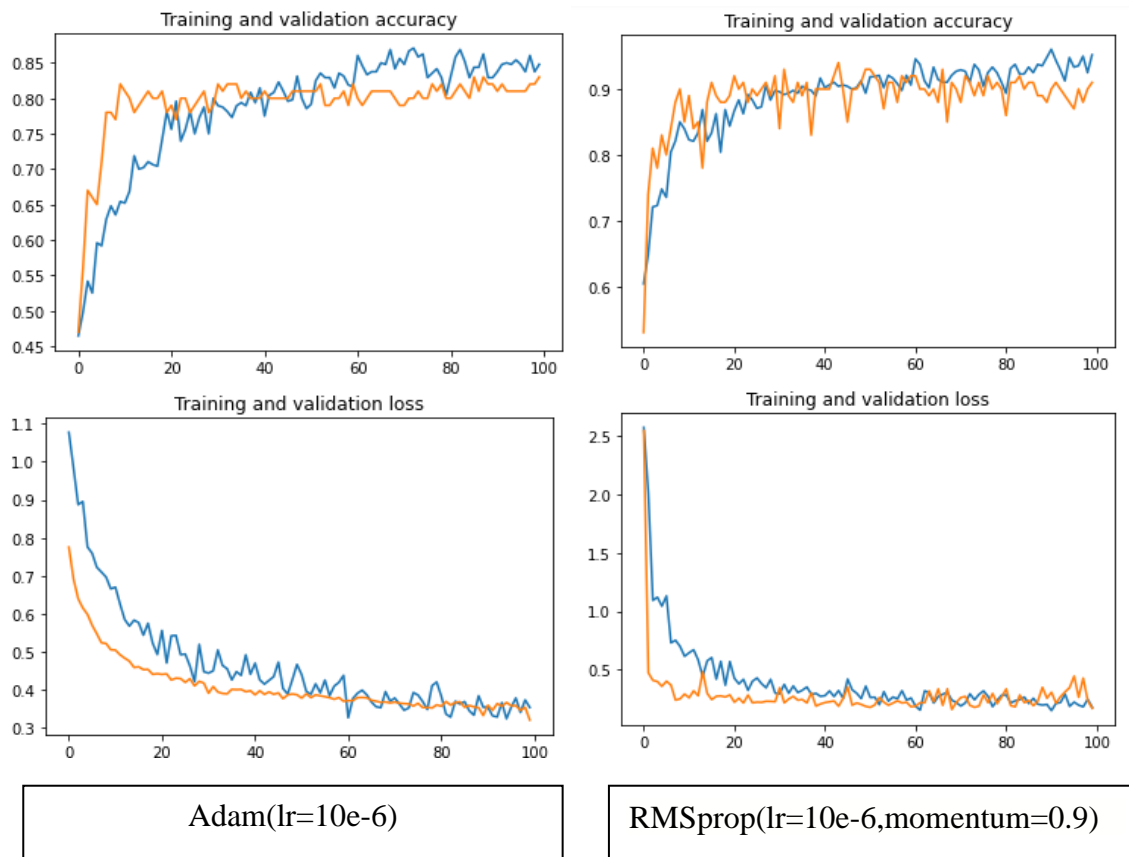


Figure IV.19: Accuracy and loss plots model 3

3.5. Results comparison table

Models	accuracy	Error	Validation accuracy	Validation error	Optimizer	Learning Rate	momentum
Model 1	71.04%	55.64%	57%	70,58%	Adam	1e-6	/
	69.58%	60.71%	60%	67.58%	RMSprop	1e-6	0.9
Model 2	89.29%	22.95%	86.27%	27.15%	Adam	1e-6	/
	88.67%	30.22%	86.07%	26.45%	RMSprop	1e-6	0.9
Model 3	84.79%	35.36%	83%	32.05%	Adam	1e-6	/
	95.21%	17.68%	91%	16.97%	RMSprop	1e-6	0.9

Table IV.1: Resultscomparaison table

Conclusion:

In this chapter, we have presented a classification approach based on pretrained convolution neural networks models, which are ResNet50 and Inception-v3, and we have shown the different results obtained in terms of accuracy and error.

General conclusion

General conclusion

In this thesis, we talked through the concepts of Artificial Intelligence with Machine learning in general and, Deep Learning with Artificial neural networks and image processing in particular. We also have introduced convolutional neural networks one of most popular type of ANNs by presenting the different types of layers used in the classification: the convolutional layer, the pooling and the fully connected layer. Moreover, we took some pre-trained CNN models.

The banks did not provide us with any help and did not allow us to take pictures of the banknotes. This is what made us work to collect the data ourselves, and that is why its size was very small.

During the training our proposed model, we encountered a problem of overfitting , that's why we used transfer learning models such us ResNet50 and Inception V3 .

Transfer learning include the saving of resources and improved efficiency when training new models, and we have already noticed this in the results that we obtained through the experiments we carried out , where Model 1 and Model 2 had much better performance than Model 1

We used the GPU of Google Colab , Unfortunately, We weren't so lucky, after all Google Colab gives us a limited GPU (12GB NVIDIA Tesla K80 GPU that can be used up to 12 hours) , Because of many attempts to train, sessions begins crashed, then restarts and then crashes again , to solve that we need to increase the limitation of GPU, , for that we need to pay for increasing.

In the end in perspective, we can already thought of increasing the number of images of the proposed dataset. And make use of a detailed study on the problem of overffiting that we have entered and this by playing on the architecture of the Convolutional part and even varying the parameters of the model, especially the Momentum. And why not propose a real automatic machine intended for the classification of the physical state of banknotes in collaboration with the banking sector and research labs.

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