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# Data Mining Techniques for Knowledge Discovery in Digital Images

*A Thesis Submitted to the Department of Computer Science, University of Anbar, College of Computer Science and Information Technology as Partial Fulfillment of the Requirements for the Degree of Master of Computer Science*

*By*

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**عنوان الرسالة:**

***Data Mining Techniques for Knowledge Discovery in Digital Images***

بِسۡمِ ٱللَّهِ ٱلرَّحۡمَٰنِ ٱلرَّحِيمِ

﴿قُلِ ٱللَّهُمَّ مَٰلِكَ ٱلۡمُلۡكِ تُؤۡتِي ٱلۡمُلۡكَ مَن تَشَآءُ
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**صدق الله العظيم**

**[سورة آل عمران، ٢٦]**

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## *Dedication*

*To those that can’t be described by words .....*
*My father and mother.*

*To the one who lived in my heart .....*
*My dear husband.*

*To those who were the support and light of*
*My way .....*
*My brothers and sisters.*

*To those who taught me.....*
*My teachers*
*I dedicate my effort .....*

***Dhamea Anwar***

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# Abstract

Advances in image acquisition and storage technology have led to tremendous growth in very large and detailed image databases. A vast amount of image data such as satellite images, medical images, and digital photographs are generated every day. These images if analyzed, can reveal useful information to human users. Unfortunately, it is difficult or even impossible for a human to discover the underlying knowledge and patterns in the image when handling a large collection of images. Image mining is rapidly gaining attention among researchers in the field of data mining, information retrieval, and multimedia databases because of its potential in discovering useful image patterns that may push the various research fields to new frontiers.

This thesis proposes a system for classification of the images by one popular type of machine learning models which is deep neural networks, where stacked layers of “neurons” are used to learn approximate representations of data the Convolutional Neural Network (CNN). This will be done in the following suggested basic steps. The first step is to use "CIFAR-10” dataset and prepare the data for a convolution neural network. The second step is insert images to the convolution layer, Relu function, pooling layer, and flatting layer. Then using the result of the second step to classify image using fully connected and softmax function. The effectivity of using convolution neural network to classification data for train accuracy (99%) and test accuracy (95%) with bach size (128) epoch (140). The proposed approach has been applied and tested on datasets "CIFAR-10”. Using 60000 images that split into three groups. First one contains 35000 images to train the model and the second contains 15000 images to validate model while the last one is 10000 images to test the model. The implementation of the propos system has done by using python programming language.

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## List of Abbreviations

| Abbreviation | Explanation |
|---|---|
| AI | Artificial intelligence |
| ANN | Artificial Neural Network |
| API | Application Programming Interface |
| BoF | Bag of Features |
| CNN | Convolutional Neural Network |
| DCNN | Deep Convolutional Neural Network |
| DNN | Deep Neural Network |
| DM | Data Mining |
| DWT | Discrete Wavelet Transform |
| FC | Fully Connected |
| IBKLG | Instance-Based K-Nearest Using Log and Gaussian |
| IM | Image Mining |
| IR | Image Retrieval |
| KNN | K-Nearest Neighbor |
| ML | Machine Learning |
| MMS | Multimedia Messaging Service |
| MRI | Magnetic Resonance Imaging |
| NN | Neural Network |
| PCA | Principal Component Analysis |
| ReLU | Rectified Linear Unit |
| RMS | Root Mean Square |
| RNN | Recurrent Neural Network |
| SIFT | Scale Invariant Feature Transform |
| SMS | short message service |
| SVM | Support Vector Machine |

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# CHAPTER 1
General Introduction

# Chapter One
# General Introduction

## 1.1 Introduction

Data mining is the process of extracting patterns from large databases in statistical and data analysis. It needs knowledge discovery technology and tools. Knowledge discovery may be the extraction of implicit, unknown, and useful information from the data. Knowledge discovery in dataset has its roots in statistics (the numeric study of data relationships), artificial intelligence (human-like intelligence displayed by software and/or machines)and machine learning (algorithms that can learn from data to make predictions). Data mining enrich the knowledge which helps to improve the quality of the decisions. Data mining applications motivated the relevant parties to be fully utilized as necessary in the acquisition of valuable information in some sectors. This sectors such as management of customer relationship, marketing, medical analysis, web mining, engineering, prediction, and mobile computing. Recently, several algorithms of data mining were developed to facilitate the processing and interpreting of large stores of data [1] as shown in figure(1.1)[2] .

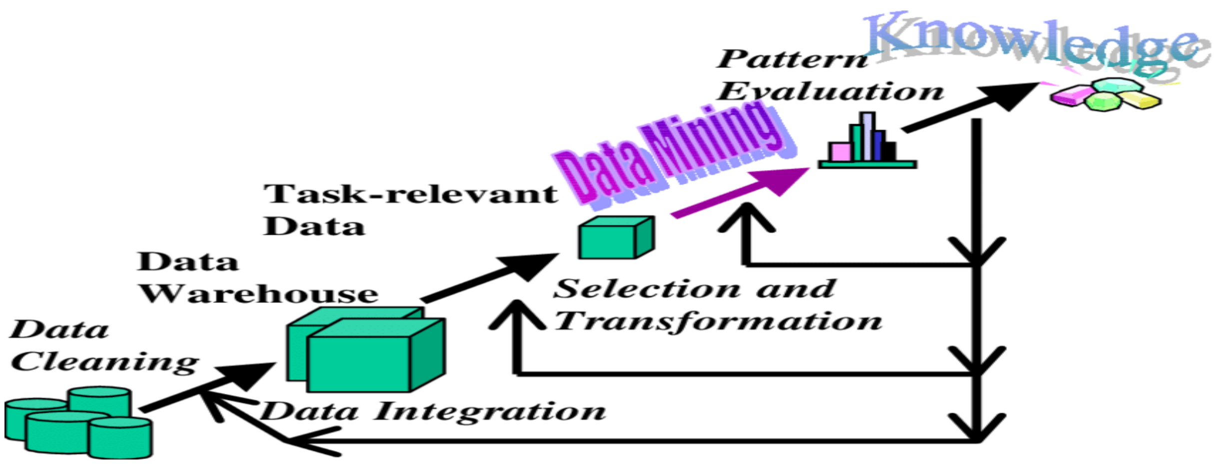


**Figure (1.1): Data Mining Process**[2]**.**

Data mining models are divided into predictive and descriptive models. The inference of the data in the predictive mining tasks is made for predictions. The forecast predictive models were established using well-known data, and the outcomes were obtained by employing the results to a data set having the same characteristics. It is made on explicit values based on patterns identified by known results. The descriptive data mining (no predicted target value) offers characteristics and describe the data set. In the descriptive models, the data mysterious patterns are extracted and utilized to make the decision. The descriptive models are mainly used for many purposes such as exploring, identifying, and exploring new ideas to be applied later [3], as shown in figure (1.2)[4].

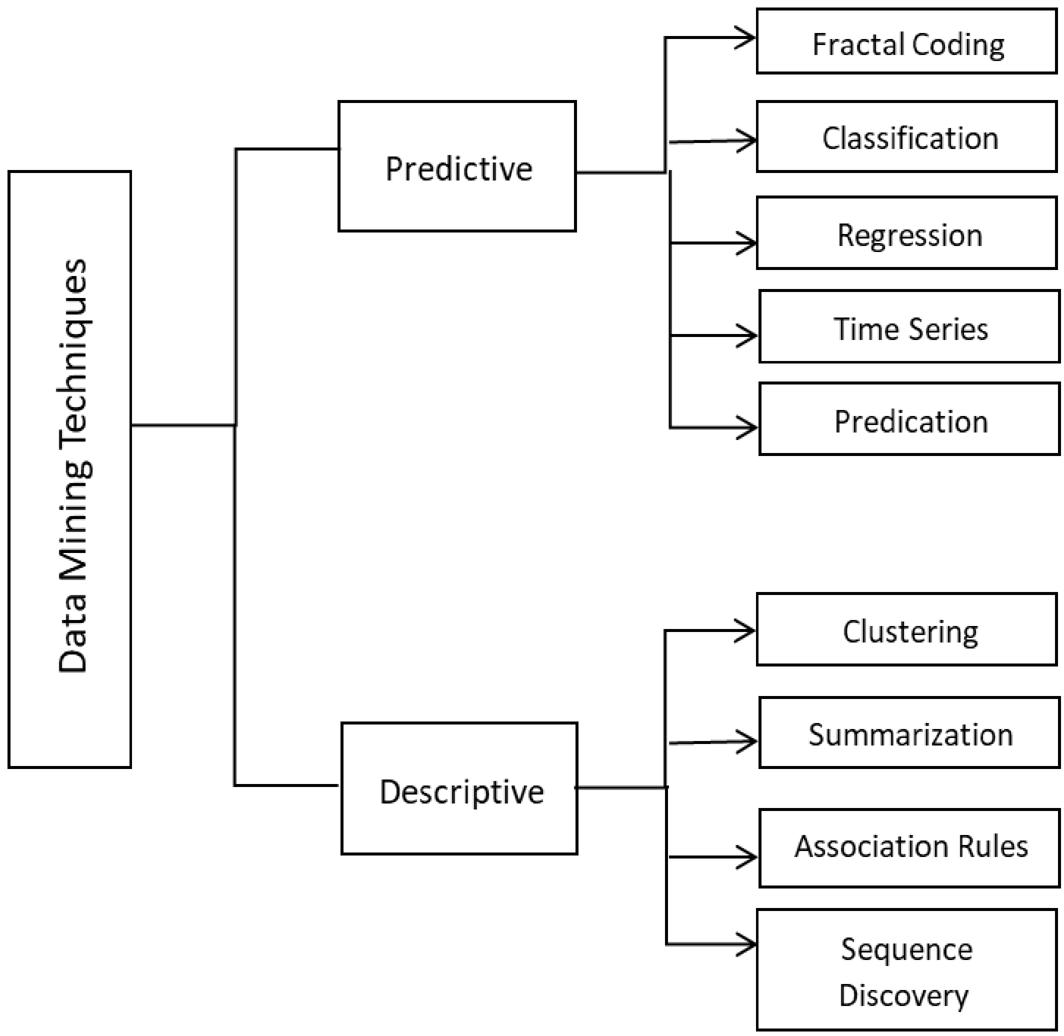


**Figure (1.2): Models of Data Mining** [4] **.**

## 1.2 Image Mining Definition

Image mining is the method of searching and discovering valuable information and knowledge in huge image data set. Image mining is based on data mining, digital image processing, machine learning, image retrieval, and artificial intelligence. Image mining is handled with the hidden information extraction, an association of image data and additional pattern which are not quite visible in the image. Image mining consists of many methods to retrieve images and try to find the most efficient route, it saves users effort [5] [6].

As a result of the inflation in the use of the social network , mining plays a vital role in dealing with a huge amount of data available in various fields such as the medical field, satellite field, business field, and so on. Image mining is different from low-level computer vision and image processing techniques because the focus of image mining is in the extraction of patterns from a large collection of images [7] The image mining technique deal with the extraction of implicit data and images with information relationships or different patterns not expressly kept within the image. Researches in image mining can be broadly classified into a specific approach. See in the following figure, methodology is used to deal with the image down to knowledge [8], as shown in See figure (1.3).

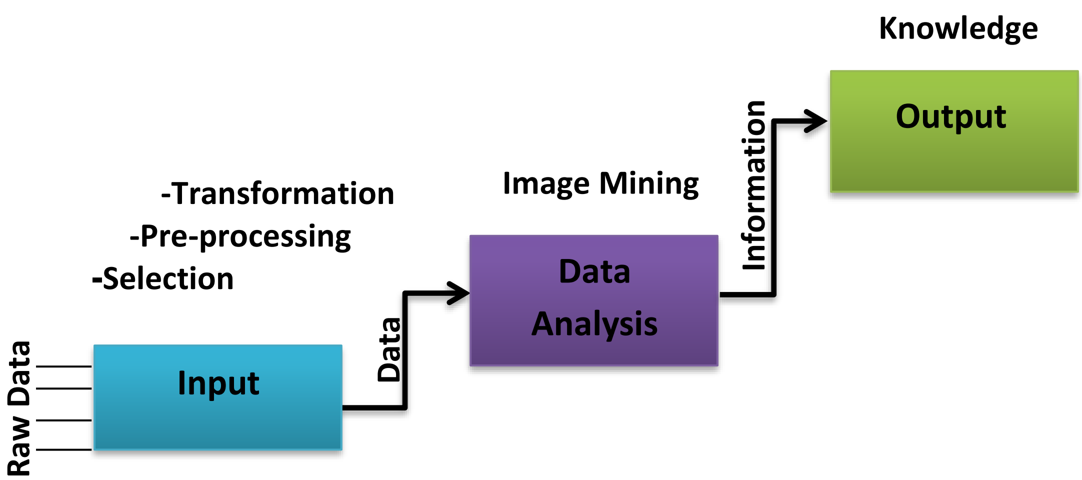


**Figure (1.3): Image Mining Architecture**

## 1.3 Knowledge Discovery

The data is not alwayes available in a simple format, but is generally in large volumes, and is dispersed across the enterprise. To benefit from this big volume of constantly evolving data, organizations must have a well-defined strategy to collect, store, synthesize, and disseminate it in the form of knowledge required for system functions. Figure(1.4) represents the three distinct concepts to reached the knowledge required for system, the data, information, and knowledge [9].

Data consists of unprocessed discrete and objective facts about events, properties of objects, etc. Data is mostly structured and has no value unless processed and analyzed [10]. Information is derived from the aggregation and analysis of data. It is used mostly to assist in decision making. Information is meant to change the way the receiver perceives something, and to have an impact on their judgment and behavior. Knowledge is know-how and is what makes possible the transformation of information into instructions. Knowledge can be obtained either by transmission from another who has it, by instructions (explicit knowledge), or by extracting it from experience (tacit knowledge). Essentially, knowledge is evaluated and organized information that can be used purposefully in the problem-solving process [11]. See figure(1.4) [12].

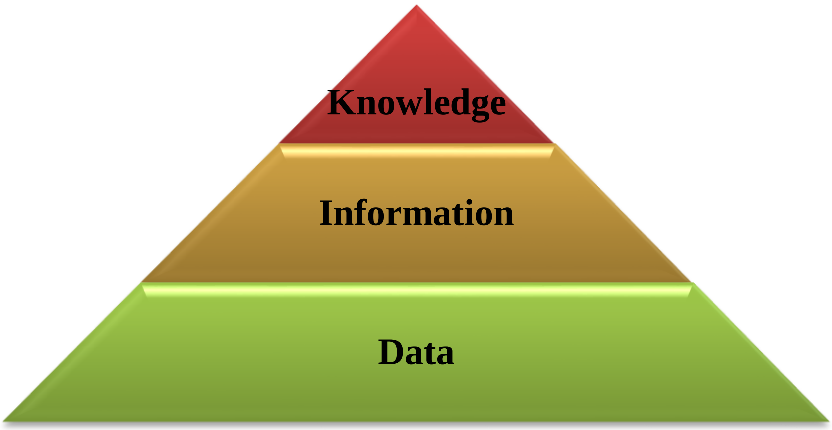


**Figure (1.4): Knowledge Discovery**[12].

## 1.4 Related work

In this part, the thesis shows the previous studies on image mining which are close and related to study.

1) R. B. V and R. K. Senapati (2016) [13] proposed utilizing color fundus images to identify the bright lesions or exudates using a computer associated with a screening system. The suspicious regions of the bright lesions were firstly detected by the screening system then the interested region under investigation was characterized by the texture feature extraction method. The last stage was performed using the support vector machine classifier to classify the images into normal and abnormal images.

2) S. Kumar et al. (2017) [14] suggested applying a hybrid approach to extract features from the images. The approach conducted the discrete wavelet transform (DWT) for that purpose, while the Genetic algorithm is used to diminish the number of features. Finally, the support vector machine (SVM) is utilized to classify the brain tumor. In comparison with the other reported techniques, an improvement in the accuracy and a minimizing in the RMS error (the similar context linear accuracy was 80%-90%) is recorded by using the hybrid approach.

3) S. Chauhan, A. More, R. Uikey, et al. (2017) [15] proposed that the MRI brain images are pre-processed by median filtering. To segregate lesions from an image, color-based segmentation and edge detection are performed. All the extracted features are stored in a transactional database to which IBkLG classifier is applied (Instance-based K-Nearest using Log and Gaussian weight Kernels) to classify the tumor into normal benign or malignant.

4) R. Duration Safiyah, Z. Abdul Rahim, et al. (2018) [16] In this paper the evaluation has been carried out using Convolutional Neural Network (CNN) models. The CNN models are simple CNN, and pre-trained CNN models (Alex Net and Google Net). The optimum results are achieved by Alex Net using dataset includes 7000 images.

5) N. N. A. A. Hamid, R. A. Razali et al. (2018) [17] compared three different models which are Conventional Convolutional Neural Network (CNN), Bag of Features (BoF) and Alexnet for fruiter cognition aiming to achieve a lower human interference in the fruit harvesting, in addition, to reduce the cost and the time of the harvesting process.

6) B. B. Traore, B. Kamsu-Foguem, et al (2018) [18] In this paper, the aouthor conducted the DCNN recognition approach to classify the microscopic images which include cholera or malaria.

7) W. Lumchanow and S. Udomsiri. (2019) [19]. This paper presents image classification algorithms to improve the learning rate and to compare the classification efficiency. Using a convolutional neural network (CNN) for feature extraction and using the k-nearest neighbor (KNN) to find appropriate k for a k-nearest neighbor. Medical datasets were used in the experiments to classify Plasmodium Vivax and Plasmodium Falciparum.

8) N. F. Sahidan, A. K. Juha et al. (2019) [20] by adopting both (CNN) and Bag of Features (BoF) and getting the benefit of the available public database called the Folio dataset. CNN exhibited a powerful feature performance in computer vision.

9) H. Sofian and S. Muhammad et al. (2019) [21] in this paper, they suggested classification of Coronary artery. The researchers conducted the available networks using Cartesian Coordinates and polar reconstructed coordinate images for a deep understanding of the ultrasound images.

10) A. A. Abdullah, A. F. D. Giong et al. (2019) [22] in this paper, for a real-time detection of cancer cells, used CNN algorithm for auto-detection. The proposed solution based on segmenting the nuclear of the cancerous cell. The detection of the algorithm was of an accuracy of about 88%.

## 1.5 Discussion and Conclusion for Related Works

Out of the Literature Review studies that consist of researches for different authors which have aforementioned in ( 1.4), can inferred the following:

**Table 1.1: Methods used in the previous related works with the proposed approach**

| NO. | Author | Years | Techniques | Number of datasets | Accuracy |
|---|---|---|---|---|---|
| 1 | R. B. V and R. K. Senapati. [13] | 2016 | Support vector machine(SVM) | 1289 image | 96% |
| 2 | S. Kumar et al.[14] | 2017 | hybrid approach:(DWT) & (SVM) | 145 image | 85% |
| 3 | S. Chauhan, A. More, R. Uikey, et al. [15] | 2017 | GLCM ,K-means clustering, IBkLG | 34 image | 86% |
| 4 | R. Durratun Safiyah[16] | 2018 | Convolutional Neural Network (CNN). | 7000 image | 65% |
| 5 | N. N. A. A. Hamid et al. [17] | 2018 | Comparing (BoG),(CNN),Alex net | 1200 image | BoG=98% Alex net=95% CNN=99% |
| 6 | B. B. Traore et al.[18] | 2018 | Convolutional Neural Network (CNN). | 240 image | 94% |
| 7 | W. Lumchanow et al.[19] | 2019 | Hybrid approach :( KNN) & (CNN). | 940 image | 89% |
| 8 | N. F. Sahidan et al.[20] | 2019 | Hybrid approach :( BoG) & (CNN). | 640 image | 82% |
| 9 | H. Sofian et al.[21] | 2019 | Convolutional neural network (CNN). | 2175 image | 85% |
| 10 | A. A. Abdullah et al.[22] | 2019 | cellular neural network | 1500 image | 88% |

Through this rapid presentation of previous studies in the classification of images, the most important conclusions in this area are the possibility of using the techniques of image exploration efficiently. With the progress in the field of digital photos, there is a huge amount of images in the data warehouses, which need to be classified and rearranged. As noted in the table (1.1), they used image are few. Therefore, seek in study to use the best algorithm that deals with a large number of images, as it can classify thousands of images with high accuracy. These techniques have evolved in the past decade in proportion to the amount of data available in all fields, and this is what continue in this study in Chapter III.

## 1.6 Problem Statement

The main problem statement of this thesis is first and foremost, the prerequisite to knowledge discovery is understanding your data and your business. Without this understanding, no algorithm, regardless of sophistication, is going to provide you with a result in which you should have confidence.

There is a weakness in general solutions in the field of object identification in the picture. As in the field of security surveillance cameras, where you need a focus on specific specifications in case of suspicion of something.One of the fundamental problems in image content analysis to efficiently recognize the environment and retrieving relevant content from a large different scene database.

## 1.7 Contribution

The concept of image mining and classification plays an important role in the future. Our contribution is summarized below:

1. Making experiments to test the best configuration of the sequential model for classifying images as means to exploit organizational knowledge, facilitate learning, and improve performance meet the needs of individuals and organizations and governments to support decision making .

2. Using the convolution neural network to build and train models of classification to obtain better performance inside the confines of traditional formal training environments of images dataset of CIFAR-10.

## 1.8 Thesis goals

The main objectives of this thesis are:

1. Designing image classifier system with performance for efficien classifying of images and can be applied in several organizations and capable of predicting image type efficiently.

2. These Patterns and rules are analyzed in order to acquire knowledge and discover new solutions by using data mining technques for digital images. Starting with entering images and ending by selecting the category to which the image belongs.

## 1.9 Thesis Structure

This thesis has four more chapters in addition to chapter one.

Chapter Two: "Image Mining Systems". This chapter explains the definition of (IM), the tools used, and the types of techniques and how they can be used. The chapter also includes the architecture explanation of Image Mining.

Chapter Three: **“**Proposed System Design". Explains the framework being proposed which will be used in the system that includes: Schema, interfaces, application, and other tools used in the design and analysis.

Chapter Four: “Performance Evaluation & Results Discussion". The chapter will discuss the implementation of the system and the results that are obtained from system implementation.

Chapter Five: "Conclusions and Future Works”. Outlines the main conclusions of the thesis and advices for works in the future.

# CHAPTER TWO

## Image Mining Systems

# Chapter Two
# Image Mining Systems

## 2.1 Introduction

Image plays vital role in many applications, mining image data one of the essential features in the present research field. Image data plays vital role in every aspect of the system such as in hospital for surgery, engineering for construction, web for application and so on. This chapter presents the background of this thesis. In the first section, image mining techniques will be discussed in detail which includes different types of techniques of mining. The second section discusses image mining architecture. Then the third section explains the machine learning and different machine learning types and. The fourth section will be a discussion about the artificial neural network architecture that includes different types of algorithms such as a convolutional neural network which is the main in this thesis.

The fifth section we will discuss multimedia data mining and their categories . the sixth section will be a discussion of world wide web for the digital images. Also, this section will display the applications of the data mining.

## 2.2 Images Mining Techniques

Various techniques to mine image information and how they are applied in image mining can be explained by object recognition, image retrieval, image indexing, image classification, image clustering, association rule mining, and neural network[23]. Figure (2.1) [24] shows image mining techniques.

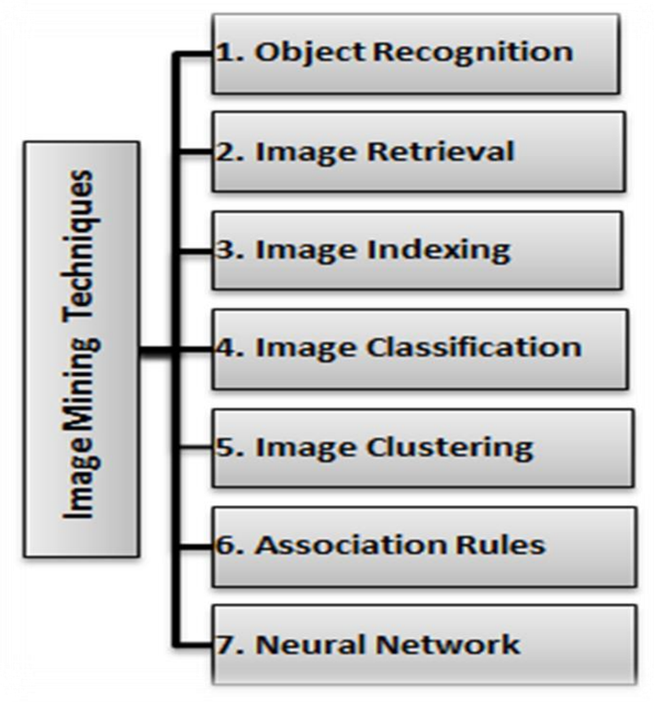


**Figure (2.1): Image Mining Techniques**[24]**.**

## 2.2.1 Object Recognition

The technique has been focused on the active research field of image processing. Using object models which might be known a priori, object models and recognition technique can find objects in actuality from images that belong to an image database. Useful information extraction and automatic machine learning can simply be realized when a few objects are identified and recognized by the machine. The object recognition problem is referred to as any supervised labeling problem depends on object models of known items [25].

## 2.2.2 Image Retrieval

With more and more information appear on the internet and the multimedia, the world focus on exact and fast retrieval. Image retrieval is classified into three levels of increasing complexity [26].

**Level 1**: Considering low-level features includes color, texture, and shape to retrieve images.

**Level 2**: Considering middle-level logical features like objects of a given type or person objects.

**Level 3**: Considering a high-level features that include attributes about the meaning of scenes depicted.

### 2.2.3 Image Indexing

The objective of image indexing is to retrieve matching images from an image database for given certain query images and know the unique features of each image [23]. Content-based indexing can be used to generate terms for the color, texture and basic spatial attributes of images.

### 2.2.4 Image Classification

Classification helps us in making decisions. The information processing which is done during classification helps to categorize all pixels in a digital image into various groups [7]. It is an overseen learning method that is utilized to rank the image on the pre-classify result.

### 2.2.5 Image Clustering

Clustering is a collection of a similar data object. The dissimilar object is another cluster. It is wayfinding similarities between data according to their characteristics. Image clustering or (unsupervised) method to classify images based on the image content with out a priori knowledge[6] .

### 2.2.6 Association Rules Mining

Association rules mining is used as an efficient tool for pattern recognition in knowledge discovery and data mining. A normal association rule algorithm works based on two main methods. The first is to find all substantial item sets that match the minimum support constraint while the second moves generates rules from each of the large itemsets that match the confidence constraint [25].

### 2.2.7 Neural Network

Neural Network is one of the techniques which are used in image retrieval and image mining. They are used for a computational system made up of simple processing units called neurons. It is usually organized into layers with a full or partial connection. The major function of associated with neuron is to receive the input values from its neighbors(the output of other neurons), evaluate an output based on it weighted input and then send the output to its neighbors [25].

## 2.3 Images Mining Architecture

The image mining process can be expressed as five essential phases.

Figure(2.2)[27]. shows the description of typical image mining process

as follows:

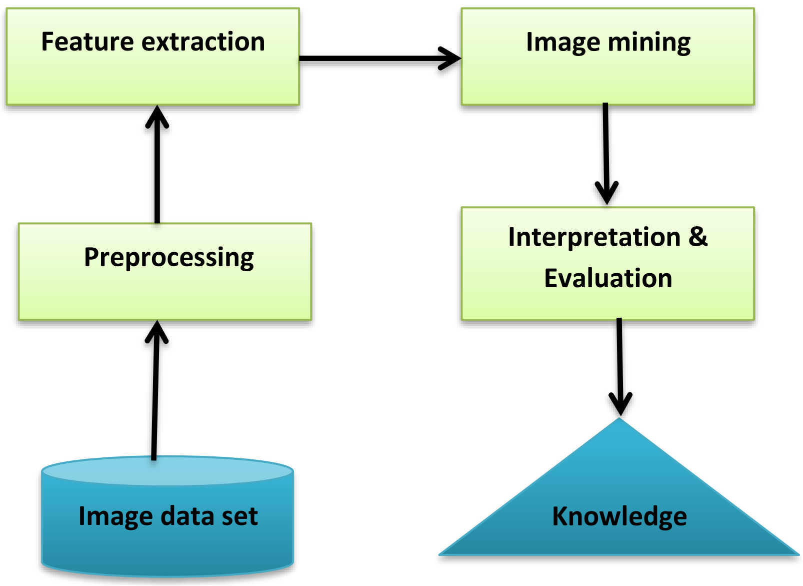


**Figure (2.2): Images Mining Steps** [27]

### 2.3.1 Image Database

In the past years, many views have been proposed in the process of classifying image databases, which are classified into the following types [11]:

**Type 1:** A very huge set of images that are collected regularly for specific functions and are accessible to many clients.

**Type 2:** A database to recover the secondary data (e.g. information of location, altitude, acquisition, quality, etc.).

**Type 3:** Imaging and mapping data management systems for spatial-oriented processing.

**Type 4:** A fundamental information database for images defining or scenes such as some graphic database systems for producing and running line drawings.

**Type 5:** A set of standard images for investigational researches of image processing algorithms or a comparison of existing algorithms.

The obtained researchers opinions for the considered images can be used for evaluating the performances of visual quality metrics as well as for comparison and design of new metrics. Quality evaluation of digital images is critical in all applications of image processing such as processing, storing, compression, and enhancement [28].

Finally, will focus in our work on **type 5** using a large set of pictures and set of collective standard images (or generally used ) for potential research, using (CIFAR -10) dataset. These dataset are used for machine-learning research. Datasets are an integral part of the field of machine learning. Major advances in this field can result from advances in learning algorithms (such as deep learning). .

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### 2.3.2 Data Preprocessing Techniques

Data preprocessing is a data mining technique that is used to transform the raw data into a useful and efficient format. It is a technique that used to improve the quality of the data before applying mining so that the data lead to high-quality mining results. The data preprocessing technique can substantially improve the overall quality of the patterns mined and/or the time required for the actual mining in the image (Image pre-processing). That can significantly increase the reliability of the optical inspection. Several filter operations that intensify or reduce certain image details enable easier or faster evaluation of some of the preprocessing techniques. Those techniques are segmentation, grayscale modification, thresholding and interpolation[24]. Raw image data directly from a camera may have a variety of problems, and therefore it is not likely to produce the best computer vision results. This is why careful consideration of image pre-processing is fundamental. Data preprocessing include data cleaning, data integration, data transformation, and data reduction. Additionally, there are some goals to the image pre-processing stage for best results such as, enhance the visual appearance of images and improve the manipulation of datasets [29]. Figure(2.3) [30] shows the pre-processing steps.

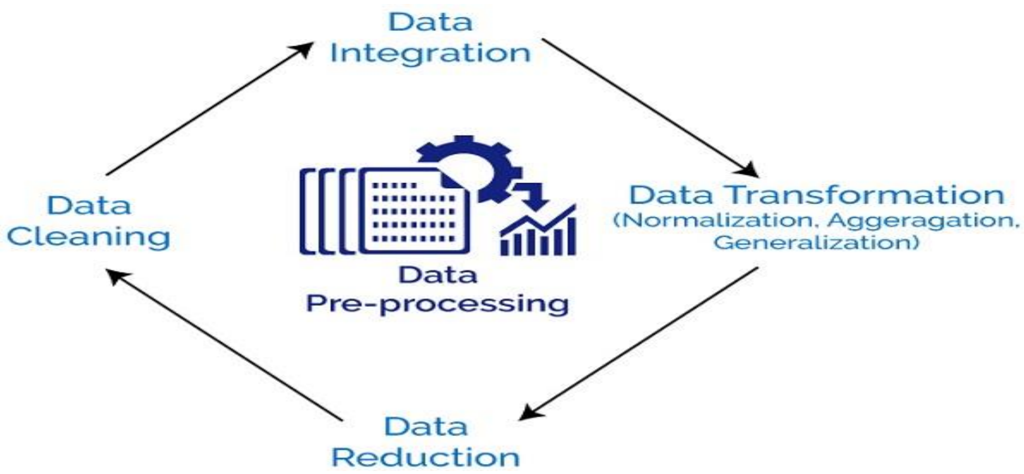



**Figure (2.3): Pre-processing Steps** [30]**.**

## A. Data Integration

Data integration involves a combination of data from different sources and heterogeneous data sources to a single, unified place. The main philosophy behind this is to make your data more actionable. Making it nice and easy for the people who are accessing it. Technology is always getting more and more advanced, and data integrity also refers to the safety of data .When the integrity of data is secure, the information stored in a database will remain complete, accurate, and reliable no matter how long it’s stored or how often it’s accessed. Data integrity also ensures that your data is safe from any outside forces[32]. Figure (2.4) [33] shows the data integration process.

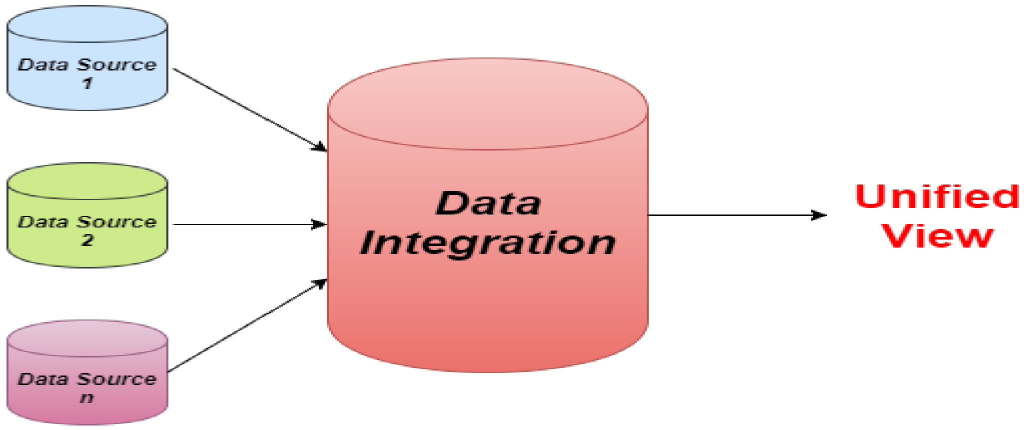



**Figure (2.4): Data Integration** [32]**.**

## B. Data Transformation

Data transformation into appropriate forms for data mining has the following contents. Smoothing data is to remove the noise from data. Aggregation is to apply summary or aggregation operations to the data. Generalization elevates the data from a low level to a higher level through the use of concept hierarchies [34]. In images acquired, images often contain deformations caused either by the camera lenses or placement. This needs digital transformation methods that are used to remove/reduce these deformations. Any minor deformations in sensed images can lead to errors in the accuracy of calculations. Usually, images can be degraded or even include artifacts [34].

## C. Data Reduction

Data reduction is the process of reducing the amount of required capacity to store data. Data reduction can increase storage efficiency and reduce costs. Data reduction techniques can be applied to obtain a reduced representation of the data set that is much smaller in volume but still contain critical information [35].

Data reduction can be achieved in several techniques:

**1. Data Cube Aggregation**: This technique is used to aggregate data in a simpler form.It summarizes the data.

**2. Dimension reduction**: Whenever we come across any data which is weakly important, then we use the attribute required for our analysis. It reduces data size as it eliminates outdated or redundant features.

**3. Data Compression**: The data compression technique reduces the size of the files using different encoding mechanisms (Huffman Encoding & run-length Encoding).

**4. Numerosity Reduction**: In this reduction technique the actual data is replaced with mathematical models or smaller representation of the data instead of actual data, it is important to only store the model parameter.

**5. Discretization & Concept Hierarchy Operation**: Techniques of data discretization are used to divide the attributes of the continuous nature into data with intervals. We replace many constant values of the attributes by labels of small intervals. This means that mining results are shown in a concise, and easily understandable way [36] .

In this study, we focus on dimensionality reduction for every input image to reduce size. It is proportional to the size of the image in the database CIFAR-10 (size image 32×32). Data compression is used to reduce the data set size because the dataset includes 60,000 images.

## D. Data Cleaning

Large volumes of structured, unstructured, and semi-structured data, are found full of noise and abnormalities. It's challenging to analyze such to better data for knowledge discovery. Also, this noise hindering semantic analysis and leading to poor customer experience. Abnormalities include non-standard characters, unstructured punctuation, different/multiple languages, and misspelled words. Worse still, people will leave "junk" text, as shown in the figure (2.5), the importance of data cleaning in digital images in removeing noise for a clearer picture, the elimination of redundancy, and reconstruction of lost data [37].

Training deep- learning neural networks are very costly. Reducing training time is an efficient way to control the activities of the neurons. In this thesis, the present normalizing the magnitude of the RGB pixel (to remove dependence on lighting geometry). The pixels of the images were normalized to values between 0 and 1.


**Figure (2.5): Data Cleaning System**

## 2.3.3 Features Extraction

Image's features play an essential factor in distinguishing and classifying a set of images into their classes. Numerous features such as color, texture, shape, edge, and boundary could be obtained from the image. Various methods have been adopted to extract the feature which will be described in details in the next subsections[38] .

.

## A. Image Edge Extraction

The features deviation of the scene such as brightness growth of the edges which are referred to the depictions of the discontinuity in the intensity function of the images. The aim of identifying the sharp discontinuities in the brightness of the image is to detect the essential and most valuable changes in the global properties. Under general hypotheses for an image, discontinuity in the image brightness might be related to the discontinuities in-depth, surface orientation, variation in properties of the material, or scene illumination changes. A variety of methods were used to distinguish those discontinuities as edges.

Edge features are Mainly essential for certain darker images. Using an edge feature individually is slightly inefficient. Therefore, it is necessary to bring it together with a stronger feature such as color. Combining with the color feature illustrates the borders and internal regions, [39]. See figure (2.6) [39] .

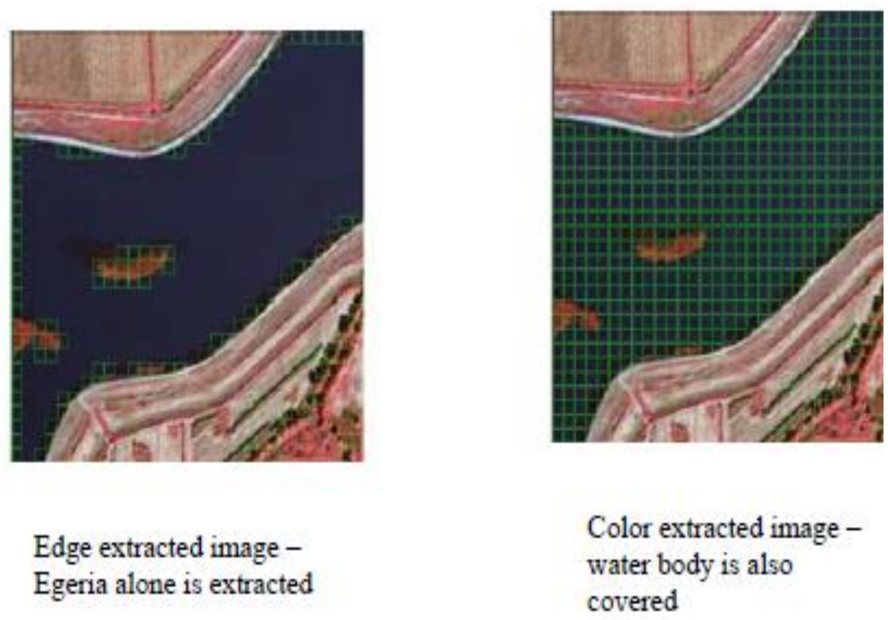



**Figure (2.6): Image Edge Extraction** [39]

## B. Image Shape Extraction

Shape is an important visual feature and it is one of the primitive features for image content description. Shape content description is difficult to define because measuring the similarity between shapes is difficult . Therefore, two steps are essential in shape based image retrieval, they are : feature extraction and similarity measurement between the extracted features [40].

## C. Image Color Extraction

Image color extraction could be utilized to obtain color as a feature of the picture. The histogram of the color feature of the image is employed to specify the image color distribution. The histogram equalization is used to control the distribution of the red, green, and blue colors in the image. The equalization process of the image based on calculating and redistributing pixels of red, green, and blue of that image to create contrast balanced in the image. This permits the area of smaller contrast to achieve greater contrast. See figure (2.7) [39] .

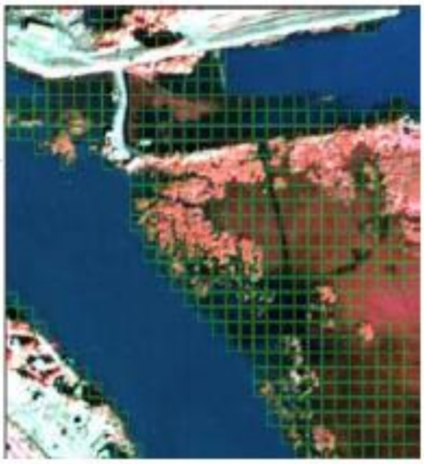


**Figure (2.7): Image Color Extraction**[39]

### D. Image Texture Extraction

The image depends on human perception and is also based on the Machine Vision System. Image Retrieval is based on the color histogram and texture. The perception of the human System of image is based on the human neurons which hold 1012 of information. The Human brain continuously learns with the sensory organs like an eye that transmits the image to the brain which interprets the images. The texture could be described as a neighborhood feature of an area or a block. The difference in each pixel regarding its neighboring pixels describes the texture. In the present case, it happens in open water or water of the beach. Thus the textural details of such similar zones would be capable to be compared with a texture template [39].

## 2.4 Machine Learning

Machine learning is defined as the field of study that provides computers with the ability to learn from input data without being explicitly programmed to do so. The learning process is done iteratively from analyzed data and new input data.

Machine learning emphasizes on automatically learning and adapting when exposed to data without the need of human intervention [41]. Five main techniques of machine learning exist which are:supervised learning, unsupervised learning, semi-supervised, reinforcement learning and finally deep learning. Figure (2.8) [42] shows the different machine learning types and that will be mentioned in details.

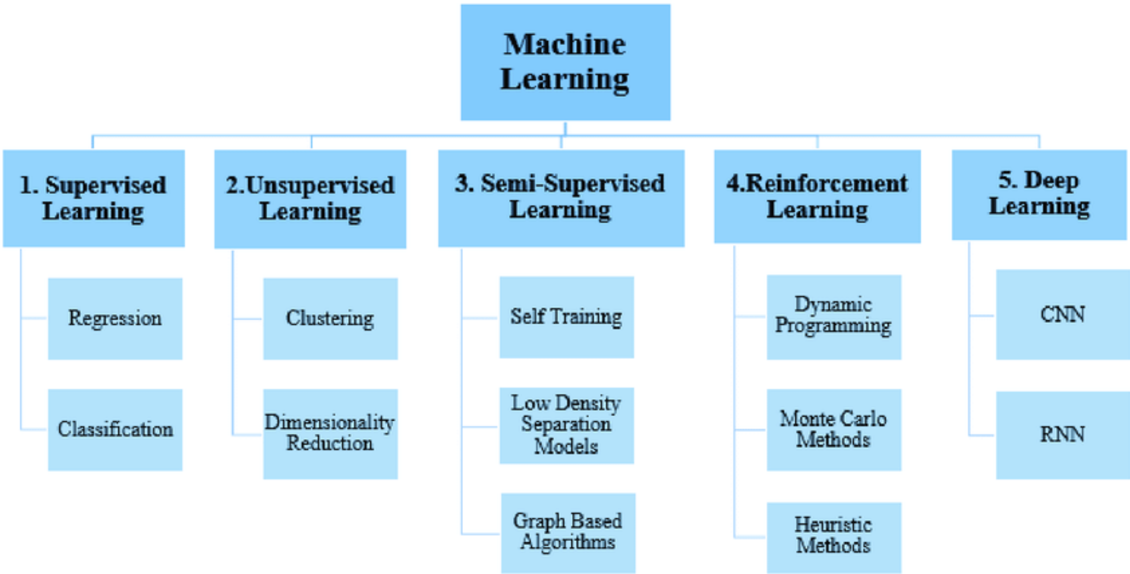



**Figure (2.8): Machine Learning Types [42]**

## 2.4.1 Supervised Learning

Supervised Learning is a kind of leaning that takes place based on labeled data to stands for the data whose class is known. The job of supervised learning is to design a classifier given a set of classified training set. The approaches of supervised image classification must have a pre-labeled dataset for training. A classifier is trained in the feature space via the training dataset and will be applied for classifying a new network image. Numerous researches were performed for solving a variety of image classification issues with the use of supervised approaches [43]. For the supervised learning (predictive model, "labeled" data), the main categories for classification task are Logistic Regression, Trees, KNN, SVM, Naive Bayes, etc.. Figure (2.9) [41] show different stages of the Supervised Learning.

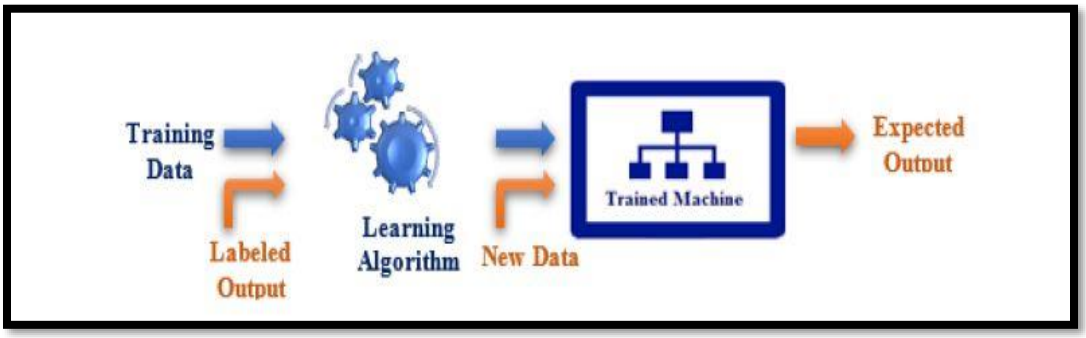



**Figure (2.9): Stages of The Supervised Learning.**[41]

## 2.4.2 unsupervised learning

In unsupervised learning , data of closer proximity of similarity are clustered together in a particular class of which label is unknown [42]**.** Unsupervised approaches detect internal correlations in the unlabeled input data. One of the main unsupervised approaches is clustering. Even though clustering requires no class labels, classifiers may be derived in the case where the image clusters are corresponding to various applications of the network[44]. For the unsupervised learning (descriptive model, "unlabeled" data) the main categories for clustering task are clustering (K-Means, PCA, etc...). Figure(2.10)[41] shows different stagesof the unsupervised learning.

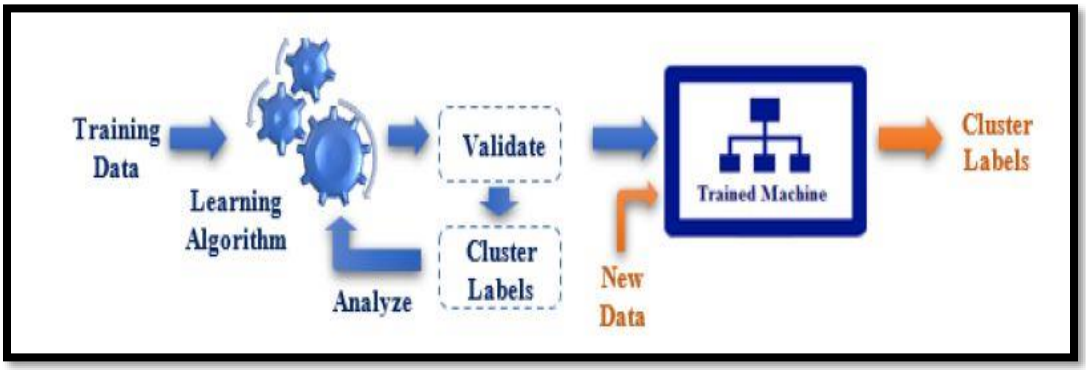



**Figure (2.10): Stages of The Unsupervised Learning.**[41]

## 2.4.3 Semi-Supervised Learning

Usually, is not easy to obtain labeled data most of the time. In the case of using the label data alone for training, the training dataset would be excessively small for entirely reflecting the characteristics of the dataset. New applications of the network are continuously developed, which results in image data with no label. Each of these situations results in issues for the conventional supervised ML approaches. For addressing this issue, the semi-supervised ML approach has emerged, because of its capability of combining unsupervised and supervised learning. In semi-supervised learning, the training dataset includes each of the samples that are labeled or unlabeled[45]. Figure (2.11) [41] show different stages of the Semi-Supervised Learning.

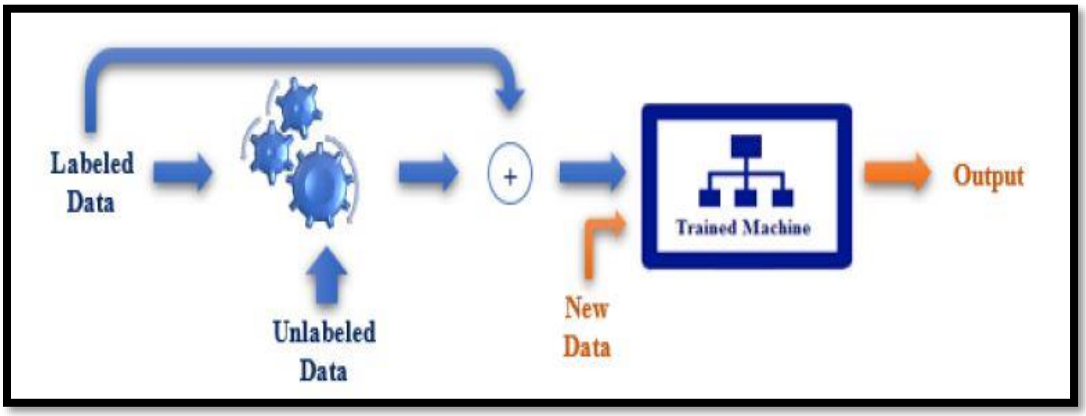



**Figure (2.11): Stages of The Semi-Supervised Learning** [41]

## 2.4.4 Reinforcement learning

Reinforcement learning is learning by interacting with theproblem environment. A reinforcement learning agent learns from its own actions rather than being specifically taught what to do. It selects current actions based on past experiences (exploitation) and new choices (exploration). Thus, it can be described as a trial and error learning process. The successof an action is determined through a signal received by the reinforcement learning agent in the form of a numericalreward value. The agent aims to learn to select actions that maximize the value of the numerical reward ment learning[46]. Figure (2.12)[43] show the reinforcement learning.

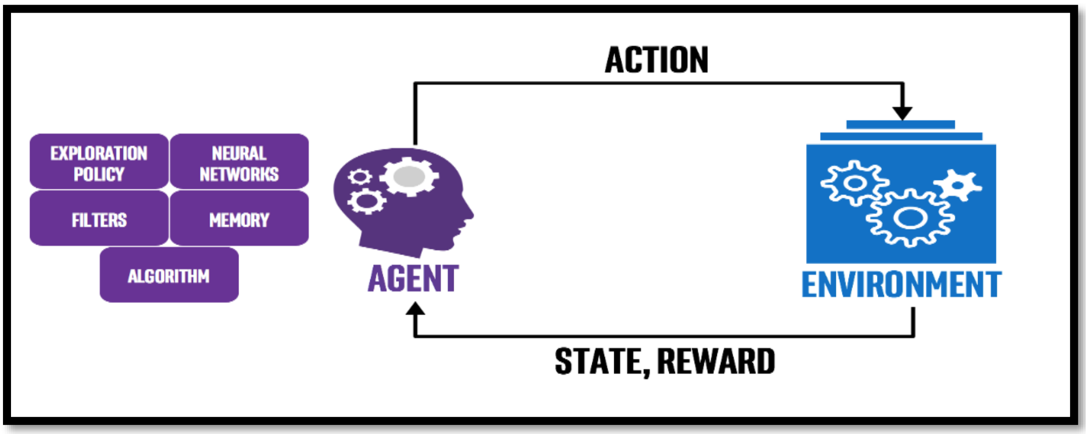



**Figure (2.12): Reinforcement learning**[43]

## 2.4.5 Deep Learning

Deep Learning can be described as a subfield of machine learning that is based on algorithms that learn from multiple of levels in order to provide a model that represents complex relations among data. Deep learning is basically the intersection point between neural networks, graphical modeling, optimization, artificial intelligence, pattern recognition as well as signal processing[41].figure (2.13)[43] show different between the machine learning and deep learning.

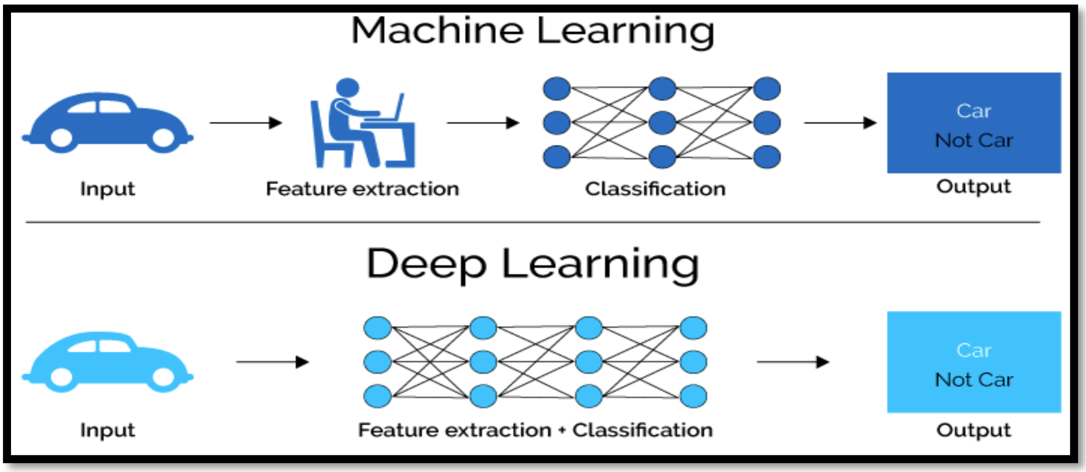



**Figure (2.13): The Machine Learning and The Deep Learning**[43]

## 2.5 Artificial Neural Network

An Artificial Neural Network (ANN) is a computational network depending on the structures and works of biological neural networks. Information that streams over the network influences the structure of the NN because neural network variations or learns, is depending on that input and output. Since it was scientifically employed, a neural network has been examined with two different scientific ways:

1. The biological investigates NNs as an easy simulation of the human brain and performs it to investigate the presumption of the human brain functions.
2. Employing NNs as a technology to hand out the sophisticated data. NNs assessed related to their implementation in operating sophisticated problems. In particular, it is operating for the prediction, association, and classification [47].

The long course of development has given the human brain many suitable features, which are not present in the Von Neumann system or modernistic parallel computers. These comprise generalization ability, huge parallelism, inherent contextual information processing, learning ability, distributed representation, and computation adaptively, consuming of low energy, and error tolerance. NN was considered to be an excellent option to deal with mysterious problems due to the advantages and capabilities to analyze incomplete noisy data [47].

### 2.5.1 Artificial Neural Network Architecture

Neurons are linked with the network and optimized in such the output of each one neuron be the feedback for one or more neurons. The link in neurons could be one-directional or bi-directional. According to the intensity, the connection can be classified as excitatory or inhibitory. Neurons structured in layers that are classified into hidden and output layers. The hidden layer collects the input data where the data is processed and delivered to the output layer neurons. In the output layer, the network output is matched with the requested output and the network error is computed. The data error moves back over the network and the values of connection loads among the neurons are modified using the error term. In order to achieve the desired output, the process is repeated for necessary loops and finally, the output is presented to the user. Neural network learning is a vital process by which the system achieves the parallel weights among the neurons. The relationship between every two neurons is estimated and strengthened depending on the value of the connection weight. For instance, neuron *i* is linked to neuron j, wij implys the connection weight from neuron *i* to neuron *j* (wji is the weight of the reverse connection from neuron *j* to neuron i). A neuron can receive many inputs connections but generate a single output to other neurons based on a transfer [48]. Figure (2.14) [49] shows the scheme for a simple neural network.as shown relationship(1)[50]

$$\text{input i}: \sum_{j=1}^{n} \text{wij (output j)} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (1)$$

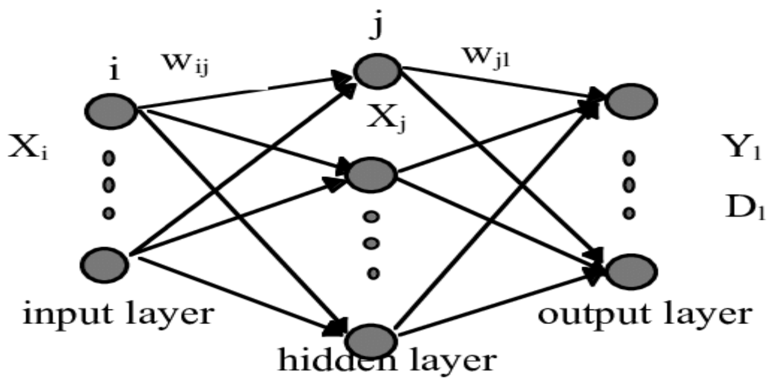



**Figure (2.14)**: **A neural network with 3 input neurons, 4 hidden neurons, and 1 output neurons**[49] **.**

## 2.5.2 Artificial Neural Network Algorithm

Each neuron collects the input data from the prior layer. The value that calculated by input data is depending on the propagation function which is usually known as a summation function. The basic summation function for the neuron i is found by multiplying the output of the neuron j with the connection weight between neurons i and j. This can be summarized for all j neurons that connected to neuron i by the following relationship (1).
where n refers to the layer's number of neurons that transmit its output to the neuron i. In other terms, the input of neuron i is the summation of output weights that access to the same neuron. In addition to the input of the standard network, the network contains two additional certain types of inputs which are the external input and bias. In external input, neuron i collects the input data from an exterior environmentwhile the value of bias is used to control the neuron activation in certain networks [50].

After receiving the input based on the summation, the output function of a neuron is computed and sent to the other neurons that it is connected to. The function of the input could be a linear or nonlinear. The transfer function is chosen in a way corresponding to the kind of problem which is needed to be solved in the network. The majority of widespread transfer functions are the tangent threshold function, hyperbolic function, linear function, piecewise linear function, and sigmoidal function. Figure (2.15)[51] .

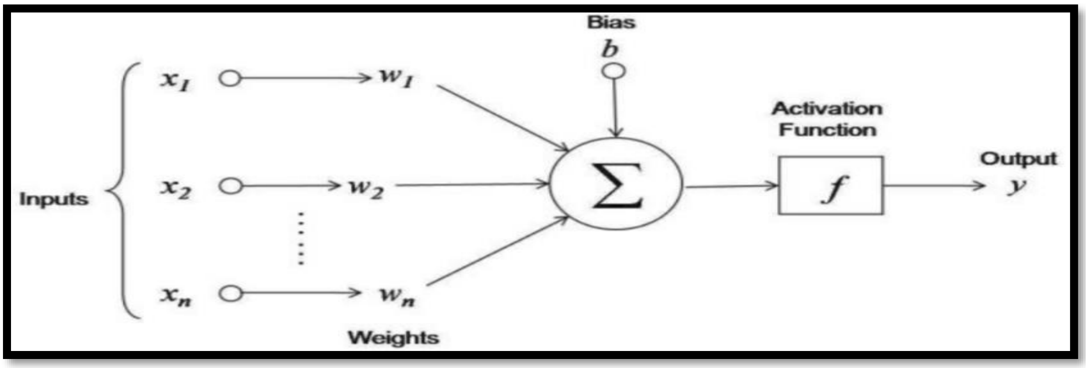
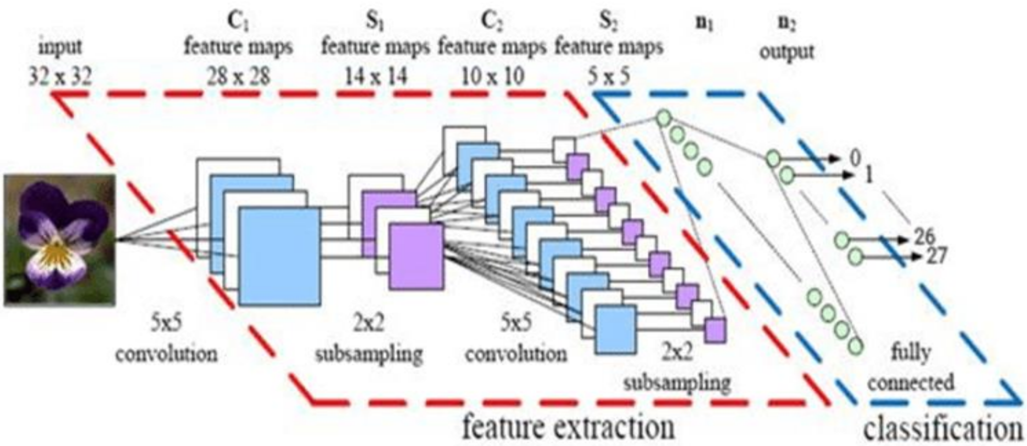



**Figure (2.15): Data processing of a neuron**[51]

## 2.6 Convolutional Neural Networks

Convolution Neural Networks (CNN) are specialized Artificial Neural Networks. CNN is well suited for the processing of images, but the same concepts are adaptable for other fields, like audio or video. CNN is widely used for computer vision. During the training process, the network building blocks are repeatedly altered for the network to reach optimal performance and to classify images and objects as accurately as possible. CNN is widely used in a modern Machine Learning as a result of its continuing effectiveness. To clarify how CNN deals with the image, consider an example of face image as input to CNN. Basic characteristics of image such as edges, shapes, bright spots, dark spots, etc., are supplied to the network through its initial layers)[52], The next layers contain shapes and objects are describing the image such as eyes, nose, and mouth. The following layer contains features that mimic the actual faces such as shapes and objects to define the human face by the network [53]. CNN fits parts instead of the whole image. Therefore, the classification process is carried out by dividing the image into smaller parts (features). CNN consists of multiple convolutions , pooling layers, and fully connected layer. A pooling layer is applied after one or multiple convolution layers. In the next sections will describe the convolution and the pooling layer, as well as fully connected layers. The hidden layers of a CNN typically consist of additional layers that can be used for more complex models as [54], shown in figure (2.16) [55].Chapter three shows that in details.




**Figure(2.16): Convolutional Neural Network** [55] .

## 2.7 Categories of Multimedia Data Mining

Categories of multimedia data mining can be classified into static media and dynamic media. Static mining techniques are applied to a fixed amount of data. Data mining is an efficient technique that classifies, organizes, and retrieves relevant information from the data based on a user's need [56]. It includes text such as generating SMS, MMS, and a digital library. In addition to text, it includes images such as medical images . Dynamic data mining is increasingly attracting attention from the respective research community. This includes audio such as music and MP3 or video (movies). Multimedia mining is the process by which huge amounts of multimedia information being analyzed to obtain patterns according to its statistical relationships [57]. Figure(2.17) shows the multimedia data mining.

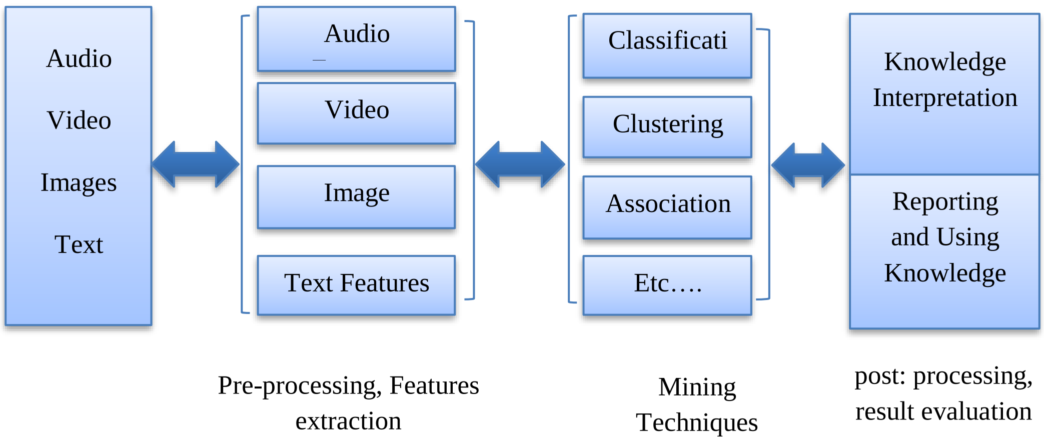



**Figure (2.17): Multimedia Data Mining**

### 2.7.1 Text Mining

Text Mining ,also referred to as text data mining, is used to find meaningful information from the unstructured texts that are from various sources. Text is the foremost general medium for the proper exchange of information. Text Mining is to evaluate the huge amount of usual language text and it detects exact patterns to find useful information [58].

### 2.7.2 Image Mining

It is a system by which the profound information or patterns of images can be extracted from massive collected images. It also clarifies how the low-level pixels can be conducted to identify high-level three-dimensional objects and relationships that consist of image processing, database, image understanding, AI, and other processes [10].

### 2.7.3 Video Mining

Video mining process is unsupported to discover fascinating patterns from a large amount of video data. Multimedia data is a video that includes images, texts, metadata, and audio. The processing is indexing, automatic segmentation, content-based retrieval, classification, and detecting triggers. It is usually used in different applications such as security, surveillance, medical applications, entertainment, sports, and learning programs [59].

### 2.7.4 Audio Mining

Audio mining process plays an essential part in multimedia applications. It can automatically search, analyze, and rotten with the wavelet transformation of an audio signal. Audio processing used features such as frequency centroid, zero-crossing rate, band energy, bandwidth, and pitch period. It is usually utilized in automatic speech identification attempting to identifying any speech in the audio [60].

## 2.8 World Wide Web for Digital Image

The World Wide Web browser was entirely text-based. The first web browser to incorporate images, took the functionality of the world wide web and allowed images to be included in the main body of the browser window [61]. This web browser was developed by the team to staff and students at the National Center for Supercomputing Applications. The ability to incorporate images into web pages increased both the web's usability and available information[62] , digital images soon became intrinsic to web design, for use as logos, banners, and backgrounds [63], as well as providing image-based content and subject matter for web pages. For those creating web pages, the ability to create and manipulate digital image data became a necessity as images were proving to be a powerful communicator in the web domain[64].

Creating digital images requires an input that converts an analog optical input into an electrical signal[65]. Creating raster digital images requires a sensor that can pick up the intensity of light for each given pixel in the grid [66].

## 2.9 Data Mining Applications

Some of the important issues in data mining include the identification of applications for existing techniques, and developing new techniques for traditional as well as new application domains, such as the Web, E-commerce, and Bioinformatics . Some of the existing practical uses of data mining are as follows:

**1. banking sector**: the purpose of this sector is for investment studies. Data mining has been successfully used in banking and finance. It is also used in the credit scoring processes [67].

**2. The medical field**: Data mining technology, as a new method of assisting disease screening and diagnosis, can help medical personnel to screen and diagnose from huge information rapidly[68] [69].

**3. Natural events**: focus on the application of data mining and analytical techniques designed so far for prediction, detection, and development of appropriate disaster management strategy based on the collected data from disasters. A detailed description of availability of data from geological observatories (seismological, hydrological), satellites, remote sensing [70] [71].

**4. Weather forecasting**: It is a critical application in meteorology and has been a standout amongst the most logically and mechanically difficult issues. The use of data mining techniques in forecasting maximum temperature, rainfall, evaporation and wind speed is increased recently.[72].

**5.Satellites:** using satellite image mining applications for the fires in forests or biological changes in sea and land [73][74].

**6. Classification of image:** the image mining consists of many methods to retrieve images and try to find the most efficient route, it saves users effort. the select a image category from among hundreds of images

# CHAPTER 3

## Proposed System Design

# Chapter Three
# Proposed System Design

## 3.1 Introduction

Convolutional Neural Networks (CNNs) have gained a remarkable success on many image classification tasks in recent years. However, the performance of CNNs highly relies upon their architectures. This thesis focuses on the design and implementation of an image classification system with high performance, where the CIFAR-10 data set is used to train models. The input of the new neural network has ten categories (number of categories in CIFAR-10 dataset). In each group, there are thousands of pictures of a model being trained and the output is what the model predicts of any input image. There are four main operations in the Convolutional Neural Network which are Convolution, Rectified Linear Unit (ReLU), Max Pooling or (Sub Sampling), and Classification (Fully Connected Layer). These operations are the basic building blocks of every Convolutional Neural Network. will try to understand the intuition behind each of these operations below. This chapter covers the following main subjects.In the first, explain the CIFAR-10 dataset and reasons for using it. This is followed by the architecture of CNN. After that, explain the method of building a classifier part. Then, the explain in details each of the layers of CNN where the outputs of each layer are the inputs for the next layer.

## 3.2 The Proposed System Structure

The proposed algorithm for the image classification consists of two models, training and testing for images dataset. The proposed system ,shown in figure (3.1), consists of many internal levels and each level is responsible for a specific task within the systemas, the CNNs are designed in two parts. , the first part is the combination of convolutional and pooling layers which is called feature extraction. The second part is known as classification which used completely connected layers. then use cost function and accurasy to measure the model. Train the model on images dataset and then test the model by read the image and resize the image , the predicating of image class by get five probabilities for each image , the high accurasy take the first probabilite . explained in details in this chapter

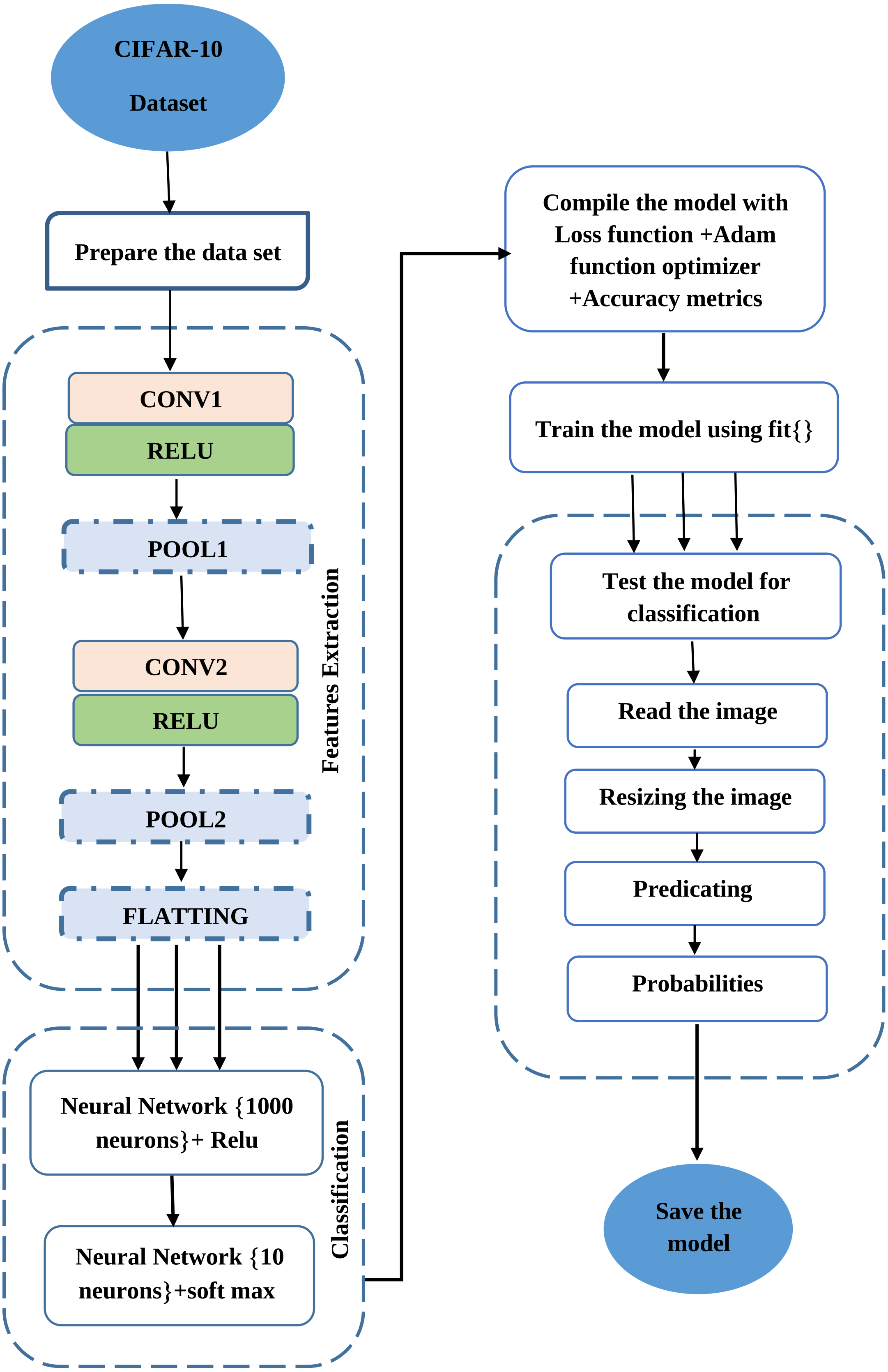



**Figure (3.1): Main Architecture of Image Classifier.**

## 3.3 Dataset

The CIFAR-10 dataset is made up of 60000 color images, each image has dimensions of 32x32 pixels. The dataset is divided into ten classes: airplane, sportscar, bird, cat, deer, dog, frog, horse, ship, and truck. Each class contains 6000 images. There are 50000 training images and 10000 test images[67] . The dataset is divided into five training batches and one test batch, each with 10000 images. The test batch contains exactly 1000 randomly-selected images from each class. The training batches contain the remaining images in random order, but some training batches may contain more images from one class than another. The reason for using the CIFAR-10 dataset is the small number of images and categories (only ten). Figure (3.2) [67]shows samples of the images in the data set.

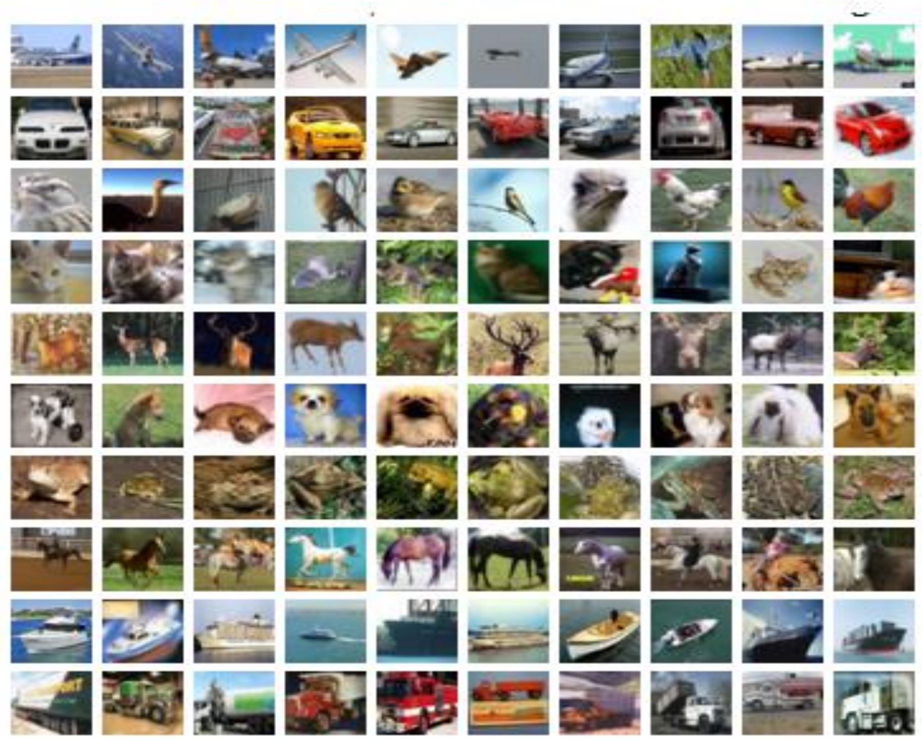


**Figure (3.2): Sample images from the dataset for ten classes** [67]**.**

:

## 3.4 Dataset Preparation

The (CIFAR-10) dataset is conveniently provided to us as part of the Keras library, so we can easily load the dataset. X_train and X_test will contain the images, and y_train and y_test will contain the digits that those images represent, will plot the first image in our dataset and check its size using the 'shape' function, so we will not need to check the shape of all the images and the dataset was prepared in two stages as explained in the next subsections.

### 3.4.1 One-Hot Encoded

Encoding plays a central role when in the learning of Convolutional Neural Networks. This so widespread encoding schema assumes a flat label space we need to convert the labels to a one-hot-vector encoding, that is, a vector representing each possible label with binary flags, a prediction vector with probability for each label, one-hot encoding is still the most prevalent procedure for addressing such multi-class classification tasks. It converts the labels into a set of ten numbers that correspond to the number of the labels in an attempt to organize the images to input the neural network as  shown in figure (3.3)

| index | label |
|---|---|
| 0 | **airplane** (0) |
| 1 | **automobile** (1) |
| 2 | **bird** (2) |
| 3 | **cat** (3) |
| 4 | **deer** (4) |
| 5 | **dog** (5) |
| 6 | **frog** (6) |
| 7 | **horse** (7) |
| 8 | **ship** (8) |
| 9 | **truck** (9) |
| ... | ... |
| ... | ... |

**original label data**

| label | index | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ... | ... |
| **airplane** | **1** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | ... |
| **automobile** | 0 | **1** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | ... |
| **bird** | 0 | 0 | **1** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | ... |
| **cat** | 0 | 0 | 0 | **1** | 0 | 0 | 0 | 0 | 0 | 0 | ... | ... |
| **deer** | 0 | 0 | 0 | 0 | **1** | 0 | 0 | 0 | 0 | 0 | ... | ... |
| **dog** | 0 | 0 | 0 | 0 | 0 | **1** | 0 | 0 | 0 | 0 | ... | ... |
| **frog** | 0 | 0 | 0 | 0 | 0 | 0 | **1** | 0 | 0 | 0 | ... | ... |
| **horse** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **1** | 0 | 0 | ... | ... |
| **ship** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **1** | 0 | ... | ... |
| **truck** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **1** | ... | ... |

**one-hot-encoded label data**

**Figure (3.3): One-Hot encoded**

### 3.4.2 Normalization

Training modern computation in deep neural networks is very costly. Therefore, normalizing functions of neurons is considered to reduce the training time. A currently available technique is called batch normalization which is used to distribute the summed input to a neuron. Over this thesis, we present normalizing the magnitude of the RGB pixel (to remove dependence on lighting geometry). The pixels of the images were normalized to the values between 0 and 1.

**Algorithm 3.1 Dataset Preparation**

**Input:** Original Image

**Output**: images preparation

**Start**

**Step1:** Load cifar10 dataset into the variables.

(x-train, y-train), (x-teat, y-teat) =cifar-10. Load-data ().

**Step2:** define the data type of the loaded data sets

**Step3:** get the shape of the x_train , y_train , x_test and y_test data.

**Step4:** define the size of the input image (32×32).

**Step 5:** define the dimension of dataset with (depth=3).

**Step6:** X- train, Y-train dataset are divided into ten label

**Step7:** define the One-Hot encoding aiming to transform the labels into a set of 10 numbers.This corresponds with the number of the labels in order to categorize the image to input into the neural network using the function to-categorical:

Y-train-one-hot = to-categorical(y-train).

Y-test-one-hot = to-categorical(y-test).

**Step8:** Normalizing the pixels of the images to the value between 0 and 1.

End

## 3.5 Structure of CNN

Typically, convolutional networks are constructed of three distinct types of layers. The layer can be either Convolutional, Pooling and fully connected. The formation of each type of these layers follows its own rules for the forward and backward signal propagation. Organizing the structure of individual layers do follow precise rules. However, the most recent developed CNNs are designed in two parts. Usually, the first part is the combination of convolutional and pooling layers which is called feature extraction. The second part is known as classification which used completely connected layers (see figure (2.16)).

## 3.6 Model Building Blocks

The first model in Keras is the sequential model. A sequential Keras model is a linear pipeline (a stack) of convolutional neural network layers. Keras layers are very accurate in the process of building model blocks. Therefore, in this research we used multiple Keras layers to create equivalent topological, then the layers were introduced by what calling an “add” method on an object of the sequential model.

## 3.7 Feature Extraction Module

After Dataset preparation, image is fed to a feature extraction module which composed of several convolution layers. Convolution neural network input and output are a set of array called feature maps. Each convolution neural network typically produces feature in three-steps, namely, convolution, nonlinear activation, and pooling.

### 3.7.1 Convolution Layer

Convolutional filters are designed to learn countless numbers of different filters that cannot be designed exclusively by the human hand to train filters that can treat various noise on images. Therefore, the pre-processing step does not need filters on the input image. The first step is to load images that we would like to predict. The convolution operation is performed on input with a specific filter, which is called the kernel. The output of convolution operation is typically called a feature map. The filter we pass them to a convolutional layer contains a set of filters where each filter has a height and weight and moves at a steady pace (stride) over the entire input image. In other words, the filter slides across the width and height of the input, and the dot products between the input and filter are computed at every spatial position. Learning in the first convolutional layer results in a feature map of low-level such as edges, lines, and angles, while learning in the next convolutional layer results in more complex representations, such as parts and models. The deeper the network and the more the number of features map, the higher levels and better representation of features of the input image which guarantees the accuracy of classification. See figure (2.16)

The next parameter is the shape of the input image. Images will be converted into this shape during preprocessing. If the image is black and white, it will be converted into a 1D array and if the image is colored it will be converted into a 3D array. In (CIFAR-10) input shape is passed in a tuple with the number of channels ( 3 for a colored image), and the dimensions of the 3D array in each channel .

### 3.7.2 Rectified Linear Unit (ReLU)

In this layer, we remove every negative value from the filtered image and replaces it with zero. ReLU transformation function only activates node if the input is above a certain quantity. If the input is below zero, the output sets to zero. The Rectified Linear Unit is the most commonly used activation function in deep learning models. The function returns 0 if it receives any negative input, but for any positive value x, it returns that value. So it can be written as $f(x) = \max(0, x)$ .

### 3.7.3. Pooling Layer

After obtaining features using the convolutional layer, we would next use them for pooling layer. Learning a classifier with inputs having 3+ million features can be unusuall , and can also be prone to over-fitting. To address this, we reduce the size of the features map in the pooling layer. The idea behind that assembly is to reduce the size of large matrices. Pooling is another way of reducing the dimensionality of a layer and the process is carried out using max pooling

**Max pooling**: Max pooling is a pooling operation that selects the maximum element from the region of the feature map covered by the filter. Thus, the output after max-pooling layer would be a feature map containing the most prominent features of the previous feature map.

Using this definition, max-pooling can be defined as

$$P_{Max}(x) = Max(x_i) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .. (2)$$

Max pooling is mostly used after the first convolutional layer to reduce the dimensionality of the input in classification tasks. The second method is used in our work to shrink the size of the features map as shown in the following figure (3.4).

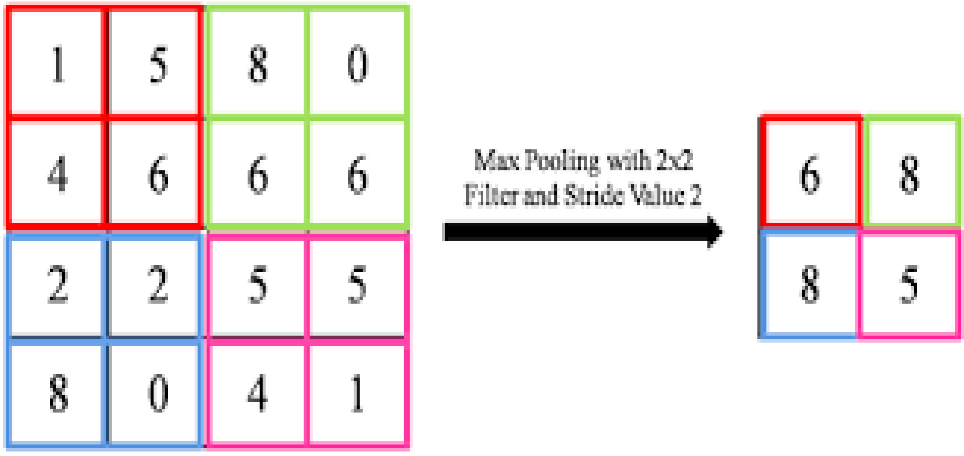



**Figure (3.4): max-pooling**

### 3.7.4 Flatting Layer

In this step, all the pooled feature maps are taken and put into a single vector. The Flatting function flattens all the feature maps into a single column.

| **Algorithm 3.2 feature extraction** |
|---|
| **Input:** images preparation<br>**Output:** the feature map |
| **start**<br><br>**Step1:** create the architecture using Sequential() .<br>**Step 2**: add the first layer, a convolution layer, create 32 (Channel) 5 (rows) x 5 (columns). strides=(1, 1)<br>**Step 3:** define activation function (relu).<br><br>A= f(z)=max(0,z)<br>$f(x) = \begin{cases} 0 & if\ \ z < 0 \\ z & if\ \ z \geq 0 \end{cases}$<br><br>**Step4:** define the input shape (32×32) with depth =3(RGB).<br>**Step5:** add max pooling (size = (2× 2)).<br>**Step6:** add the convolution layer, create 64(channel), 5(rows)x5(columns).without input shape.<br>**Step7:** add the activation function (relu).<br>**Step 8:** add the max pooling (size= (2× 2)).<br>**Step9:** add flattens model, to reduce the image to the linear array.<br>**End** |

## 3.8 Classification Module

The feature extracted by the feature extraction module is the input to the classification module for classification image. The classification module finally outputs the category of the image. The classification module usually contains full connection layers and softmax activation.

### 3.8.1 Fully Connected Layer

A Fully connected layer is the actual component that does the discriminative learning in a Deep Neural Network. The flatten layer takes the output from the previous max-pooling layer and converts it to a 1D array to enable it be fed into the fully connected layer. It's a simple multi-layer perceptron that can learn weights that identify an object class. If the classification is being performed, a fully connected layer is added, where the neurons in the fully connected layer have full connection to all activation in the previous layer. Adding this layer allows the classification of the that input described by feature maps and extracted by the previous layers. See figure (3.5).

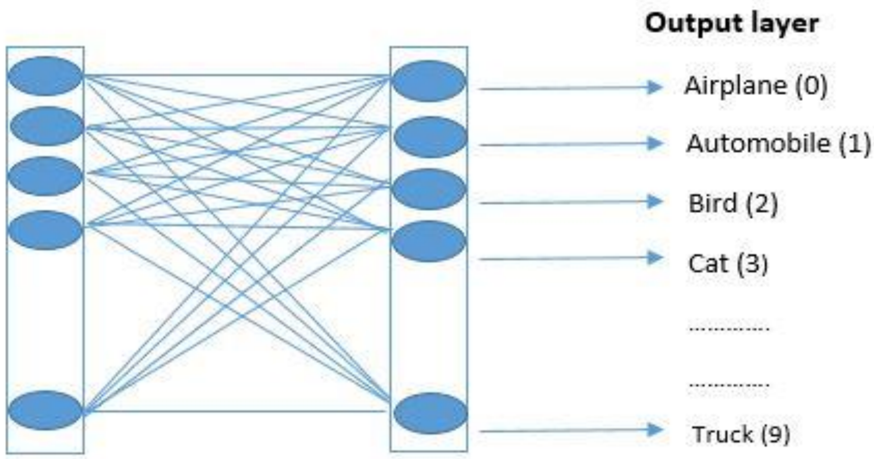



**Figure (3.5): Fully Connected Layer**

### 3.8.2 Softmax Activation Function

The softmax function is often used in the final layer of a neural network-based classifier. Softmax is a very interesting activation function because it is not only maps our output to a [0, 1] value but also maps each output in such a way that the total sum is 1. To understand this better, think about training a network to recognize and classify the dataset that divided into ten class's images. The network would have ten output units, one for each class. If you fed an image of a dog class to the network, the output unit corresponding to the dog classes would be activated. Each training image is labeled with a true digit and the goal of the network is to predict the correct label.

## 3.9 Model Compilation

When the structure of the model is specified before it can be trained, it also needs to have a cost function, optimization procedure, and metrics defined. This is done by calling the compile method on the model.

| **Algorithm 3.3 classification algorithm** |
|---|
| **Input:** feature map<br>**Output:** Compile the model |
| **Start**<br>**Step1:** create a neural network<br>**Step2:** add the first layer has 1000 neurons and activation function (rule).<br>**Step3:** add the last layer has 10 neurons (one for each label) and activation function (softmax).<br>$\text{Softmax}(X_i) = \frac{exp(X_i)}{\sum_j exp(X_j)}$<br>**Step4:** Compile the model. The compile function takes three parameters:. model.compile =['accuracy']).<br>$\text{Accuracy}= \frac{Number\ of\ correct\ prediction}{Total\ number\ of\ prediction\ made}$<br>**Step 5**: Model . compile (Loss= 'categorical_crossentropy')<br>Probability that the element belongs to class 1( or positive class)=p<br>Probability that the element belongs to class 0 ( or negative class)= 1-p<br>Then, the cross-entropy loss for output label y (can take values 0 and 1) and predicted probability p is defined as:<br>$Loss = \begin{cases} Log(1-P), & if\ \ y=0 \\ Log(P)\quad , & if\ \ y=1 \end{cases}$<br>**End** |

A loss function is the objective that the model will try to minimize. It can be the string identifier of an existing loss function (such as categorical_crossentropy or mse). a list of metrics. For any classification problem you will want to set this to metrics=['accuracy']. A metric could be the string identifier of an existing metric (only accuracy is supported at this point).

## 3.10 Model Fitting

Model fitting is the measure of how well a machine learning model generalizes data similar to that with which it was trained. Fitting method loads the entire dataset at once and uses it to train the network. It splits the data into training data (70%) and testing data(30%).

| **Algorithm 3.4 train the model** |
|---|
| **Input:** image data set<br>**Output:** test the model. |
| **Start**<br>**Step1:** train the model on training data<br>Hits=model. Fit(x-train-train, one-hot)<br>Batch-size=…….<br>Epoch=…….<br>Validation-split=0.3<br>**Batch:** total number of training examples present in a single batch.<br>**Epoch:** number of iteration when an entire dataset is passed forward and backward through neural only once.<br>**Validation:** initialized with data for testing data.<br>**Step2:** visualize the model accuracy for both the training and validation data.<br>**Step3:** visualize the model loss for both the training and validation data**.**<br>**Step4:** test the model. Load the data that you want to classify from an image file into the variable.<br>**Step 5:** resize the image to 32×32 pixels (to fit the model) with depth=3.show figure (3.6).<br>**Step 6:** get the probabilities for each class and store it into a variable. |

**Step7:** add the label of the classes to an array in the index of the label corresponding equivalent number for example" airplane" will be located at index=0.

**Step 8:** sort the probabilities from least to greates.

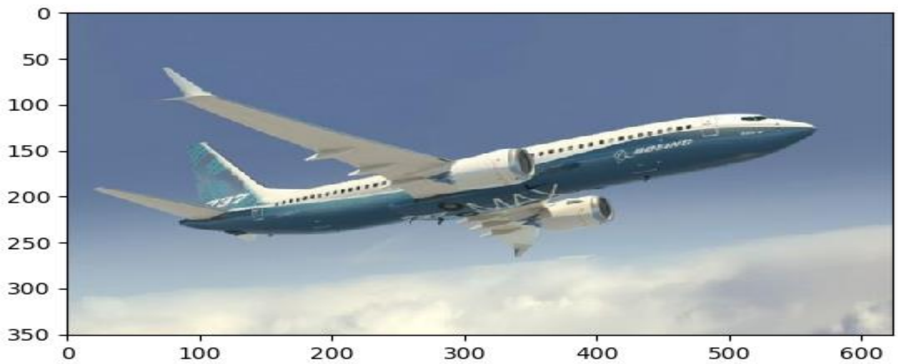
**Step9:** print the first five most likely classes.

**Step10**: Decision making depends on the expert

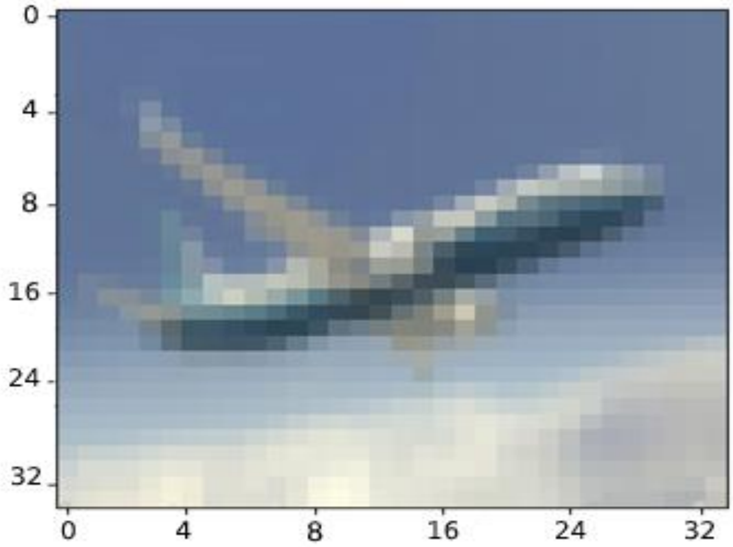
**Step 11:** save the model.

**End.**

Train the model using the fit() method which is (another word for train). Train the model on the training data (with batch size =different number , epochs =10) and Split the data into training on 70% of the data and using the other 30% as validation. Visualize the models accuracy and loss for both the training and validation data. Load the data that you want to classify from an data set. Resize the image to a 32 x 32 pixel image with depth = 3, and show the figue (3.6), then Print the first 5 most likely classes and the corresponding probability.




(A)




(B)

**Figure(3.6):(A) original image,(B) resize the image to 32×32 pixels**

# CHAPTER 4

## Performance Evaluation

## and Results Discussion

# Chapter Four

# Performance Evaluation and Results Discussion

## 4.1 Introduction

The experimental evaluation of the computer vision and pattern recognition (CVPR) algorithms is an attempt to measure the capability of the algorithms to meet the requirements. The performance of a convolution neural network classifier is identified by using a variety of metrics. The accuracy and loss are both valuable metrics for classifying images. This chapter presents the experimental results and the evaluated measures that are used for image mining.

## 4.2 Building the Model and Training setup

The training/test set is applied to split the dataset into 70% : 30%. The model was trained data for diferent epochs number. The Kernel weights were adjusted (see Table 4.1) apart from the last layer where softmax is utilized. Table 4.1 gives the detail of the architecture. Bear in mind that the database decides the number of input and output channels. The size of the inserted image for CIFAR-10 is 32 px×32 px . The model is trained by 35000 samples, validated by 15000 samples, and tested using on 10000 samples, can see figure (2.16).

The output of first convolution the layer is ((size- kernel)+ stride), (32-5)+1=28. The parameter of the layer is (((kernel * channel)+stride)* size), ((5*5)*3)+1)*32)= 2423. The output of the max pooling layer is ( output of convolution / stride ), (28 / 2)=14. The no parameter in this layer.the output of the second convolution layer is (14-5)=1=10, the parameter of the layer (((5*5)*3)+1) *46)=51264. The output of the second max pooling layer is (10/2)= 5. The output of the flatten layer is ( 5*5)*46)=1600.

**Table (4.1): Building Model Training**

| | Layer(Input) | Output | Para# |
|---|---|---|---|
| **1** | Conv2d-1(conv2D) | ( 28 , 28, 32 ) | 2432 |
| **2** | Max-pooling-1(maxpooling2D) | (,14 , 14 , 32) | 0 |
| **3** | Conv2d-2(conv2D) | (10 , 10 , 64) | 51264 |
| **4** | Max-pooling2d-2(maxpooling2D) | (5 , 5 , 64) | 0 |
| **5** | Flatten-1(flatten) | 1600 | 0 |
| **6** | Dense-1(Dense) | 1000 | 1601000 |
| **7** | Dense-2(Dense) | 10 | 10010 |
| **8** | Total params: 1,664,706<br>Trainable params: 1,664,706<br>Non-Trainable params: 0 | | |

## 4.3 Model Training Results

After selecting the main parameters of architecture for CNN as shown in table 4.1, four experiments have conducted by using CIFAR 10 dataset to train and test the models with varies batch size and epoch as eplained next:

### 4.3.1 The First Experiment

Table 4.2 shows a training model in batch of size 64 and 10 epochs. The rows in this table represent ten training rounds of the model. The columns of this table are as follows: The first, second, third, and fourth columns represent the number of trains, the loss, accuracy, and time of each train respectively.

**Table (4.2):Training Model-Batch Size 64, Epoch 10**

| Training No | Loss / % | Accuracy / % | Time |
|---|---|---|---|
| Train 1 | 15% | 43% | 3:11ms |
| Train 2 | 12% | 57% | 3:11ms |
| Train 3 | 10% | 63% | 3:10ms |
| Train 4 | 9% | 68% | 3:10ms |
| Train 5 | 7% | 72% | 3:10ms |
| Train 6 | 6% | 77% | 3:10ms |
| Train 7 | 5% | 81% | 3:10ms |
| Train 8 | 4% | 85% | 3:10ms |
| Train 9 | 2% | .89% | 3:10ms |
| Train 10 | **2%** | **91%** | 3:10ms |

The above table has shown that the values of accuracy and time gradually increased in the first experement. The highest accuracy value was in the last step (91%), whereas quite the opposite was with loss value (2%). This is an evidence of network stability, but there is slowness in the model implementation. Model accuracy at test was 66%. The model accuracy and model loss have shown in figures 4.1 and 4.2 respectively.

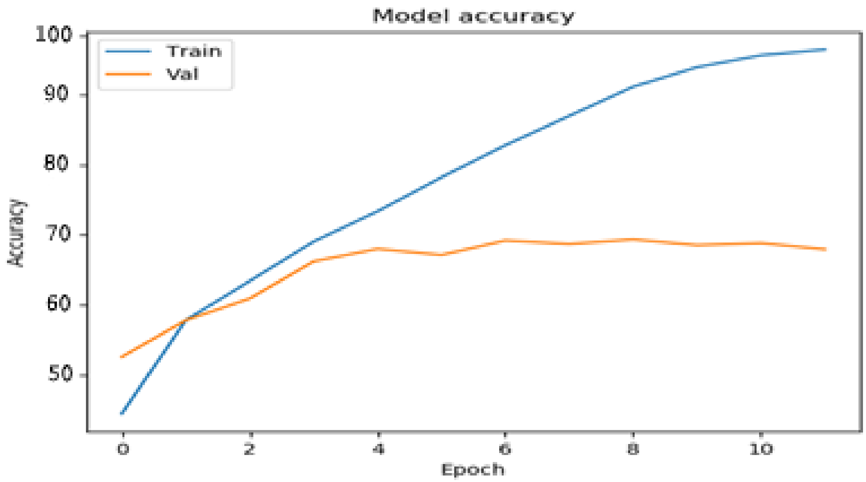



**Figure (4.1): Model Accuracy when batch size 64 and epoch 10.**

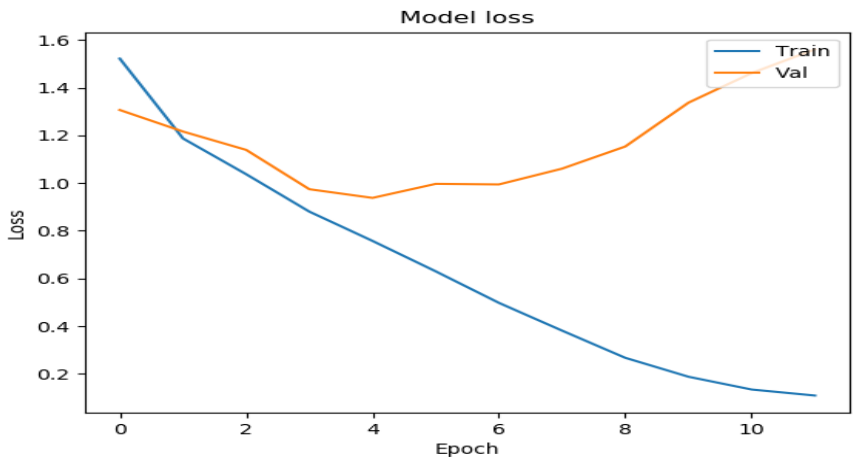



**Figure (4.2): Model Loss when batch size 64 and epoch 10.**

### 4.3.2 The Second Experiment

Table 4.3 shows a training model in batch of size 128 and 10 epochs. The rows in this table represent ten training rounds of the model. The columns of this table are as follows: The first, second, third, and fourth column represent the number of trains, the loss, accuracy, and time of each train respectively.

**Table (4.3):Training Model-Batch Size 128, Epoch 10**

| Training No | Loss / % | Accuracy / % | Time |
|---|---|---|---|
| Train 1 | 15% | 43% | 3:50ms |
| Train 2 | 12% | 57% | 3:50ms |
| Train 3 | 10% | 63% | 3:50ms |
| Train 4 | 9% | 68% | 3:51ms |
| Train 5 | 8% | 71% | 3:51ms |
| Train 6 | 6% | 75% | 3:51ms |
| Train 7 | 5% | 79% | 3:52ms |
| Train 8 | 4% | 83% | 3:52ms |
| Train 9 | 3% | 87% | 3:52ms |
| Train 10 | **2%** | **90%** | 3:52ms |

The above table has shown the values of accuracy and time increased gradually in first experiment. The highest accuracy value was in the last step (90%) whereas quite the opposite was with loss (2%). This is an evidence of network stability, but there is slowness in the model implementation. Model accuracy at test was 68%. The model accuracy and model loss have shown in figures 4.3 and 4.4 respectively.

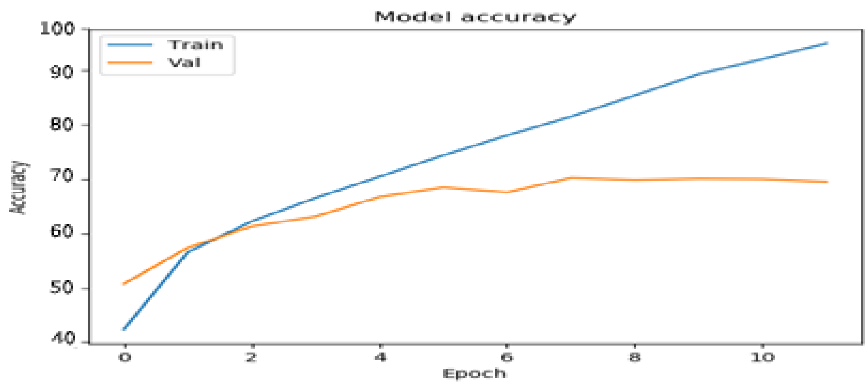



**Figure (4.3): Model Accuracy when batch size 128 and epoch 10**

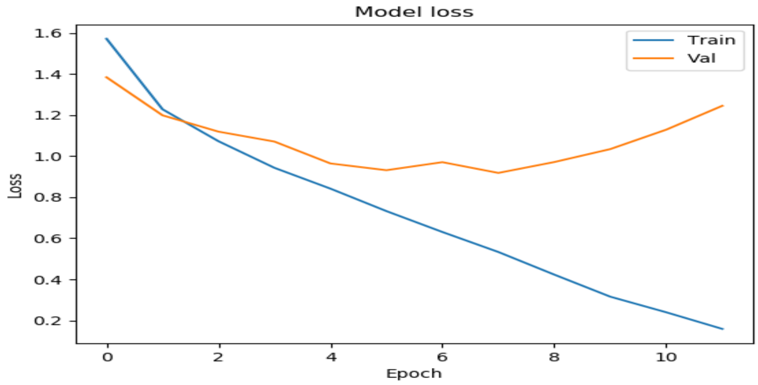



**Figure (4.4): Model Loss when batch size 128 and epoch 10**

### 4.3.3 The Third Experiment

Table 4.4 shows a training model in batch size of 256 and 10 epochs. The rows in this table represent ten training rounds of the model. The columns of this table are as follows: The first, second, third, and fourth column represent the number of trains, the loss, accuracy, and time of each train respectively.

| Training No | Loss / % | Accuracy / % | Time |
|---|---|---|---|
| Train 1 | 16% | 40% | 2:57ms |
| Train 2 | 13% | 53% | 2:59ms |
| Train 3 | 11% | 59% | 2:59ms |
| Train 4 | 10% | 62% | 2:59ms |
| Train 5 | 9% | 66% | 2:59ms |
| Train 6 | 8% | 69% | 2:59ms |
| Train 7 | 8% | 72% | 2:60ms |
| Train 8 | 7% | 75% | 2:60ms |
| Train 9 | 6% | 78% | 2:60ms |
| Train 10 | **5%** | **80%** | 2:60ms |

The above table has shown the values of accuracy and time increased gradually in first experiment. The highest accuracy value was in the last step (80%) whereas quite the opposite was with loss (5%). This is an evidence of network stability, but there is slowness in the model implementation. Model accuracy at test was 64%. The model accuracy and model loss have shown in figures 4.5 and 4.6 respectively.

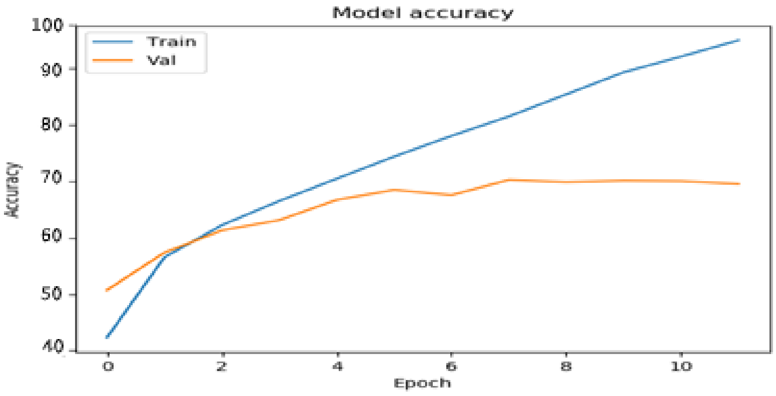



**Figure (4.5): Model Accuracy when batch size 256 and epoch 10**

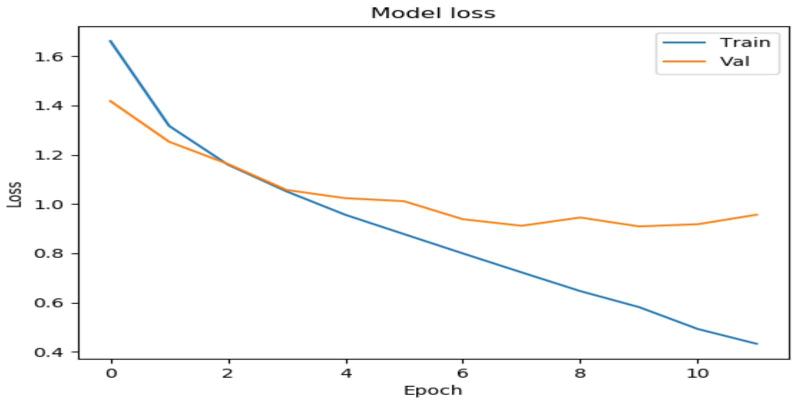



**Figure (4.6): Model Loss when batch size 256 and epoch 10**

## 4.3.4 The Fourth Experiment

Table 4.5 shows a training model in batch of size 512 and 10 epochs. The rows in this table represent ten training rounds of the model. The columns of this table are as follows: The first, second, third, and fourth column represent the number of trains, the loss, accuracy, and time of each train respectively.

**Table (4.5):Training Model-Batch Size 512, Epoch 10**

| Training No | Loss / % | Accuracy / % | Time |
|---|---|---|---|
| Train 1 | 18% | 34% | 2:50ms |
| Train 2 | 14% | 49% | 2:50ms |
| Train 3 | 12% | 54% | 2:50ms |
| Train 4 | 11% | 58% | 2:50ms |
| Train 5 | 10% | 61% | 2:53ms |
| Train 6 | 10% | 64% | 2:53ms |
| Train 7 | 9% | 66% | 2:53ms |
| Train 8 | 8% | 69% | 2:53ms |
| Train 9 | 8% | 70% | 2:55ms |
| Train 10 | **7%** | **73%** | 2:55ms |

The above table has shown the values of accuracy and time increased gradually in first experiment. The highest accuracy value was in the last step (73%) whereas quite the opposite was with loss (7%). This is an evidence of network stability, but there is slowness in implementation. Model accuracy at test was 64%. The model accuracy and model loss have shown in figures 4.7 and 4.8 respectively.

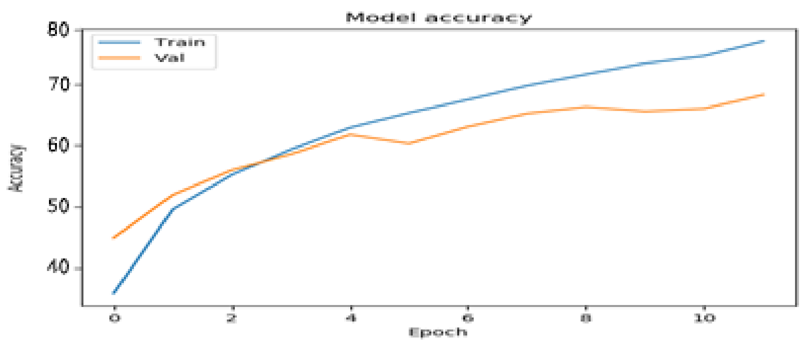



**Figure (4.7): Model Accuracy when batch size 512 and epoch 10**

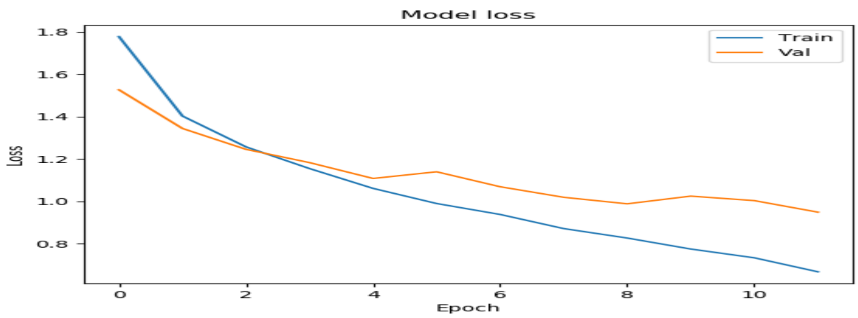



**Figure (4.8): Model Loss when batch size 512 and epoch 10**

From the results that have obtained from the four experiments, the best model accuracy was 90% and the best test accuracy was 68% for the batch of size 128. On the other hand, the worst model accuracy was 73% and the worst test accuracy was 61% for the batch of size 512 . We have concluded that when the batch size has increased more than 128 the efficiency of the model has decreased gradually. The justification for this gradual decrease is that the number of images that have entered in each training after the batch reaches size 512 was big. Consequently, the model could not distinguish all features in the input images.

### 4.3.5 The Fifth Experiment

Depending on the results of above experiments that showed the best results of model accuracy has been acheivedt with batch size of 128, we have conducted a number of experiments on the model after fixing the batch size to 128 images with a variable number of epochs in order to determine the best epoch that has obtained highest training accuracy.

**Table (4.6):Training Model-Batch Size 128 with variable epochs**

| Batch size | Epoch No. | Accuracy training |
|---|---|---|
| 128 | 10 | **90%** |
| 128 | 20 | **92%** |
| 128 | 30 | **95%** |
| 128 | 140 | **99%** |

The results of four experiments have been summarized in table 4.6, where the batch size was constant in all experiments but the epoch was variable from one to anthor experiment. Note that at the last experiment when epoch was 140 the model has obtained 99% accuracy obtained 95% test accuracy , which is higher compared to other experiments with less epochs number. This is because that when the system has been trained with a large number of epochs, the model has become more stable. In addition to stability, the efficiency of the model in image recognition has been increased.

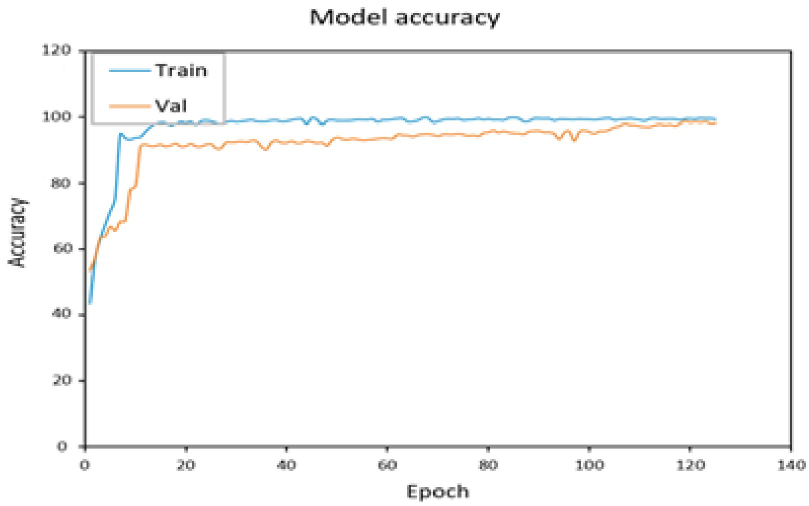



**Figure (4.9): Model accuracy when batch size 128 and epoch 125**

## 4.4 Model Examination Results

The results of examining the model on a set of images are viewed and discussed in this section. The model have been examined on different four cases. In all those cases, the batch size was set to 128 but epochs were set to 10, 20,30 and 125 depending on the accuracy of the images entered to the model.

### 4.4.1 The Results of the First Examination

In the first examination for model with 10 epochs and batch of size 128, the results have been obtained from the model on a set of images that were randomly chosen as shown in figure (4.10).

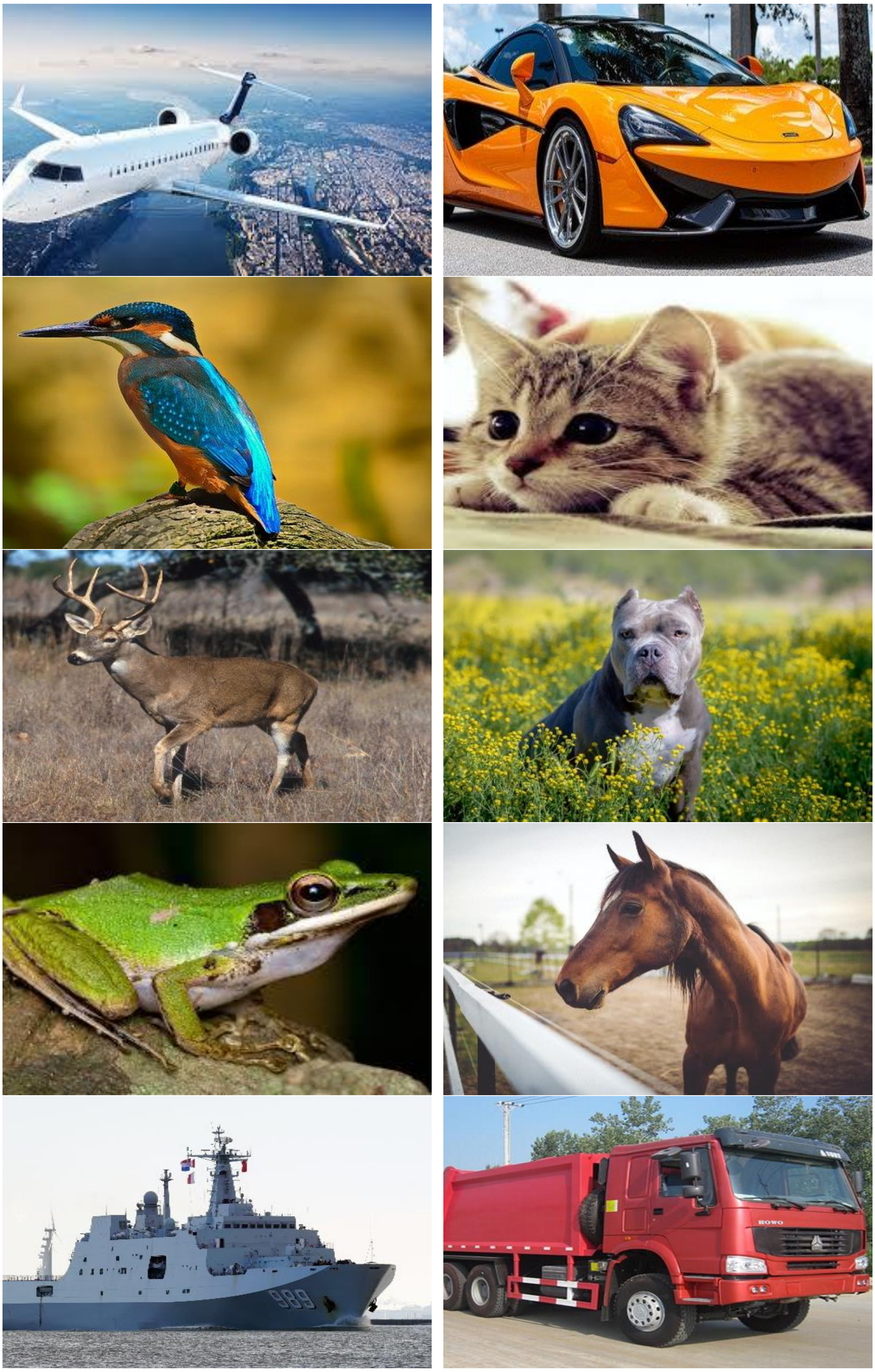


**Figure (4.10): An example of images with a colored background used in the test**

The table (4.7) below shows five predictions with the highest probability ratios based on 10 classes that representing the classes within a structure of Cifar 10 dataset.

**Table (4.7): Results of examining the model with batch of size 128 and 10 epochs**

| Classes | | The five predictions | | | | |
|---|---|---|---|---|---|---|
| | | **First** | **Second** | **Third** | **Fourth** | **Fifth** |
| 1 | **Airplane** | (airplane) 0.5307544 | (ship) 0.43500984 | (bird) 0.019086309 | (automobile) 0.0101332115 | (truck) 0.0021057175 |
| 2 | **Automobile** | **(**automobile) 0.8585728 | (truck) 0.14129873 | (airplane) 7.671742e-05 | (cat) 2.559613e-05 | (ship) 1.7210505e-05 |
| 3 | **Bird** | (bird) 0.9891017 | (dog) 0.004354195 | (cat) 0.003951391 | (airplane) 0.0019121406 | (deer) 0.00027048594 |
| 4 | **Cat** | (cat) 0.5275506 | (frog) 0.19001871 | (dog) 0.15297367 | (bird) 0.06584648 | (horse) 0.03557601 |
| 5 | **Deer** | (deer) 0.680673 | (frog) 0.097559944 | (bird) 0.09702317 | (cat) 0.07551123 | (dog) 0.030915715 |
| 6 | **Dog** | (bird) 0.9811695 | (dog) 0.007300491 | (deer) 0.0053736637 | (cat) 0.005042951 | (airplane) 0.0008130283 |
| 7 | **Frog** | (frog) 0.9950577 | (bird) 0.001748676 | (deer) 0.0016829586 | (cat) 0.0014858375 | (airplane) 1.8633637e-05 |
| 8 | **Horse** | (cat) 0.5952356 | (dog) 0.22478712 | (bird) 0.10812904 | (horse) 0.037889656 | (deer) 0.024118545 |
| 9 | **Ship** | (ship) 0.9645591 | (airplane) 0.015262814 | (bird) 0.008530175 | (cat) 0.005245037 | (automobile) 0.0029429817 |
| 10 | **Truck** | (truck) 0.95756537 | (automobile) 0.04148083 | (airplane) 0.0004735992 | (frog) 0.00027073312 | (cat) 0.0001000435- |

From the above table, can conclude that the model has predicted all images that have entered into it, except Dog and Horse. The model has given highest predictions for 4 images, which are Bird, Frog, Ship, and Truck, with following ratios 98%, 99%, 96%, and 95% sequentially. In addition, the model has recognized four of the images which are Airplane, Automobile, Cat, and Deer by giving them acceptable accuracy percentages ranging from 52% to 85%. Whereas the model has not recognized two imeges which are Dog and Horse by giving them the lowest accuracy percentages. Think that the model with more epochs, will be better in image prediction process. Therefore, we have conducted the next exam on the model with 20 epochs.

## 4.4.2 The Results of the Second Examination

In the second examination for model with 20 epochs and batch of size 128, the results have been obtained from the model on a set of images that were randomly chosen as shown above in figure (4.10).

The table (4.8) below shows five predictions with the highest probability ratios based on 10 classes that representing the classes within a structure of Cifar 10 dataset.

**Table (4.8): Results of examining the model with batch of size 128 and 20 epochs**

| Classes | | The five predictions | | | | |
|---|---|---|---|---|---|---|
| | | **First** | **Second** | **Third** | **Fourth** | **Fifth** |
| 1 | **Airplane** | (airplane) 0.9954515 | (ship) 0.0041019223 | (deer) 0.0003582769 | (bird) 6.775498e-05 | (cat) 7.525324e-06 |
| 2 | **Automobile** | (automobile) 0.53288335 | (truck) 0.46711668 | (cat) 4.2508442e-19 | (deer) 1.778738e-22 | (dog) 3.4242527e-23 |
| 3 | **Bird** | (bird) 0.9983089 | (dog) 0.0014588444 | (airplane) 0.00023204977 | (horse) 1.995245e-07 | (cat) 4.299917e-09 |
| 4 | **Cat** | (cat) 0.78060156 | (dog) 0.17456837 | (horse) 0.03466857 | (frog) 0.009755844 | (bird) 0.0003211665 |
| 5 | **Deer** | (deer) 0.9659281 | (dog) 0.026940037 | (bird) 0.0033184767 | (frog) 0.0030574142 | (cat) 0.0004396277 |
| 6 | **Dog** | (bird) 0.9999825 | (airplane) 1.4895197e-05 | (dog) 2.42842e-06 | (cat) 2.1296516e- | (horse) 1.2804295e- |
| 7 | **Frog** | (frog) 0.9999975 | (bird) 2.5422667e-06 | (cat) 2.3999186e-1 | (airplane) 1.2429782e-10 | (automobile) 7.161903e-12 |
| 8 | **Horse** | (dog) 0.72099006 | (horse) 0.27863526 | (deer) 0.000292691 | (truck) 5.4099804e-0 | (frog) 1.926644e-05 |
| 9 | **Ship** | (ship) 0.9989365 | (automobile) 0.0005669767 | (airplane) 0.00022764922 | (truck) 0.00017939713 | (frog) 3.3437846e-05 |
| 10 | **Truck** | (truck) 0.99999416 | (automobile) 5.8501637e-06 | (airplane) 6.8979705e-10 | (ship) 4.9940718e-11 | (deer) 3.6243098e-12 |

From the above table, can conclude that the model has also predicted all images that have entered to, except Dog and Horse. The model has given highest predictions for 6 images, which are Airplane, Bird, Deer, Frog, Ship, and Truck, with following ratios 99%, 99%, 96%, 99%, 99% and 99% sequentially. In addition, the model has recognized two of the images which are Automobile and Cat by giving them acceptable accuracy percentages ranging from 53% to 78%. Whereas the model has not recognized two imeges which are Dog and Horse by giving them the lowest percentages.

The results of model with 20 epochs have been compared with previous results of model with 10 epochs , and have noted that the efficiency of the model on classification has been increased with increment of the number of epochs. This is because when model has been trained on more epochs, it has acquired more knowledge which comes from increasing the number of training time for each image. Thus, this will give the model a greater opportunity to obtain the best sample that represents the image during the training period.

think that the model with more epochs, will be better in image prediction process. Therefore, we have conducted the next test on the model with 30 epochs.

### 4.4.3 The Results of the Third Examination

In the third examination for model with 30 epochs and batch size of 128, the results have been obtained from the model on a set of images that were randomly chosen as shown above in figure (4.10).

The table (4.9) below shows five predictions with the highest probability ratios based on 10 classes that representing the classes within a structure of Cifar 10 dataset.

**Table (4.9): Results of examining the model with batch of size 128 and 30 epochs**

| Classes | | The five predictions | | | | |
|---|---|---|---|---|---|---|
| | | **First** | **Second** | **Third** | **Fourth** | **Fifth** |
| 1 | **Airplane** | (airplane) 0.989121 | (ship) 0.010835928 | (truck) 3.753456e-05 | (cat) 2.7936856e-06 | (dog) 2.7096135e-06 |
| 2 | **Automobile** | (automobile) 0.8086522 | (truck) 0.19134775 | (airplain) 1.3625981e-27 | (dog) 4.599729e-31 | (bird) 8.2080674e-32 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 3 | **Bird** | (bird) 0.9158318 | (airplain) 0.084160194 | (dog) 5.531653e-06 | (cat) 2.4314531e-06 | (frog) 4.5474974e-10 |
| 4 | **Cat** | (cat) 0.9812708 | (dog) 0.014353762 | (frog) 0.003924239 | (bird) 0.00038297 | (deer) 6.159809e-05 |
| 5 | **Deer** | (deer) 0.9944944 | (dog) 0.0047119763 | (cat) 0.00045808466 | (horse) 0.00021403962 | (frog) 7.155591e-05 |
| 6 | **Dog** | (bird) 0.9989367 | (dog) 9.291507e-08 | (airplain) 4.2838035e-08 | (cat) 2.9277372e-08- | (frog) 8.613903e-11- |
| 7 | **Frog** | (frog) 0.9999999 | (deer) 1.2119601e-07 | (automobile) 3.1629106e-08 | (cat) 7.550405e-10 | (bird) 2.6637909e-10 |
| 8 | **Horse** | (horse) 0.99540174 | (dog) 0.0040384205 | (cat) 0.00048072456 | (deer) 6.1561936e-05 | (bird) 1.5531872e-05 |
| 9 | **Ship** | (ship) 0.99967015 | (airplaine) 0.00032860297 | (truck) 1.1608247e-06 | (bird) 2.2283464e-08 | (deer) 3.6512582e-09 |
| 10 | **Truck** | (truck) 1.0 | (automobile) 2.4359145e-14 | (airplane) 1.487049e-22 | (cat) 4.5283386e-26 | (frog) 2.395259e-26 |

From the above table can conclude that the model has also predicted all images that have entered to, except Dog. The model has given highest predictions for 8 images, which are Airplane, Bird, Cat, Deer, Frog, Horse ,Ship, and Truck, with following ratios 98%, 91%, 98%, 99%, 99%, 99%, 99% and 100% sequentially. In addition, the model has recognized one of the images which are Automobile by giving it acceptable accuracy percentage which is 80%. Whereas the model has not recognized one imege which is Dog by giving it the lowest percentages.

The results of model with 30 epochs have been compared with previous results of model with 20 epochs , and have noted that the efficiency of the model on classification has been increased with increment of the number of epochs. This is because, when model has been trained on more epoch, it has acquired more knowledge which come from increasinge the number of training time for each image. Thus, this will give the model a greater opportunity to obtain the best sample that represents the image during the training period.

We think that the model with more epochs, will be better in process of prediction of images. Therefore, have conducted the next exam on the model with 125 epochs.

### 4.4.4 The Results of the Fourth Examination

In the fourth test, examine the model with 125 epochs and batch of size 128. The results have obtained from the model on a set of images that were randomly chosen as shown above in figure (4.10).

The table (4.10) below shows five predictions with the highest probability ratios based on 10 classes that representing the classes within a structure of Cifar 10 dataset.

**Table (4.10): Results of examining the model with batch of size 128 and 125 epochs**

| Classes | | The five predictions | | | | |
|---|---|---|---|---|---|---|
| | | **First** | **Second** | **Third** | **Fourth** | **Fifth** |
| 1 | **Airplane** | (airplane) 0.99964976 | (ship) 0.00034798536 | (truck) 2.238384e-06 | (cat) 2.7936856e-06 | (dog) 2.7096135e-06 |
| 2 | **Automobile** | (automobile) 1.0 | (truck) 0.19134775 | (airplain) 1.3625981e-27 | (dog) 4.599729e-31 | (bird) 8.2080674e-32 |
| 3 | **Bird** | (bird) 1.0 | (airplain) 3.145949e-20 | (dog) 1.905087e-22 | (cat) 2.4314531e-06 | (frog) 4.5474974e-10 |
| 4 | **Cat** | (cat) 1.0 | (dog) 5.4029396e-11 | (frog) 9.422841e-24 | (bird) 0.00038297 | (deer) 6.159809e-05 |
| 5 | **Deer** | (deer) 0.9944944 | (dog) 0.0047119763 | (cat) 0.00045808466 | (horse) 0.00021403962 | (frog) 7.155591e-05 |
| 6 | **Dog** | **(bird) 0.9989367** | (dog) 9.291507e-08 | (airplain) 4.2838035e-08 | (cat) 2.9277372e-08- | (frog) 8.613903e-11- |
| 7 | **Frog** | (frog) 1.0 | (deer) 1.2119601e-07 | (automobile) 3.1629106e-08 | (cat) 7.550405e-10 | (bird) 2.6637909e-10 |
| 8 | **Horse** | (horse) 1.0 | (dog) 0.0040384205 | (cat) 0.00048072456 | (deer) 6.1561936e-05 | (bird) 1.5531872e-05 |
| 9 | **Ship** | (ship) 1.0 | (airplaine) 0.00032860297 | (truck) 1.1608247e-06 | (bird) 2.2283464e-08 | (deer) 3.6512582e-09 |
| 10 | **Truck** | (truck) 1.0 | (automobile) 2.4359145e-14 | (airplane) 1.487049e-22 | (cat) 4.5283386e-26 | (frog) 2.395259e-26 |

From the above table can conclude that the model has also predicted all images that have entered to, except Dog. The model has producedthe highest predictions for 9 images, which are Airplane, Automobile, Bird, Cat, Deer, Frog, Horse ,Ship, and Truck, with following ratios 99%, 100%, 100%, 100%, 99%, 100%, 100%, 100 and 100% sequentially. Whereas the model has not recognized one imege which is Dog by giving it the lowest accuracy percentages.

The results of model with 125 epochs have compared with previous results of model with 30 epochs and have noted that the efficiency of the model on classification has increased with the incrementof the number of epochs. This is because, when model has trained with more epochs, it has accured more knowlege through increase the number of training time for each image. Thus, this will give the model a greater opportunity to obtain the best sample that represents the image during the training period.

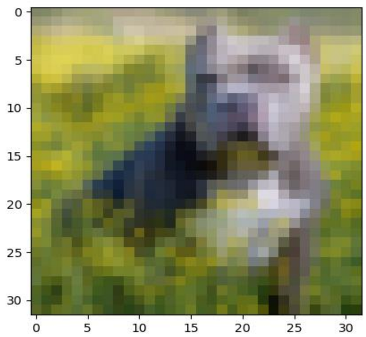
After conducting the four tests, noticed that the model's knowledge to images recognition have been increased with the increment of the number of training times and this was clear through the correct prediction of the input images . After checking all the input images for testing the model, the results showed that all the images were close to the sample of images that the model was trained on. However, still one image (Dog image) that was not recognized by the model. This is due high resolution and massive background in this image. Which leads to losing the main characteristics of the image during the process of resizing in the test phase. To mitigate those effects, crop part of the background for the dog image and reduced it to an appropriate size before repeate the test and the results were as shown in the table (4.11).

**Table (4.11): The results of examining the model with three Dog's images with different sizes**

| Classes | | The five predictions | | | | |
|---|---|---|---|---|---|---|
| | | **First** | **Second** | **Third** | **Fourth** | **Fifth** |
| 1 | **Dog-1 Size 1024*580 pix** | (bird) 0.9413345 | (deer) 0.058665488 | (cat) 4.153306e-08 | **(dog) 5.720304e-13** | (horse) 2.1536271e-22 |
| 2 | **Dog-2 Size 483*524 pix** | **(dog) 0.608206** | (cat) 0.39179403 | (deer) 3.5710985e-15 | (bird) 1.1097019e-16 | (horse) 2.0628685e-17 |
| 3 | **Dog-3 Size 50*48 pix** | **(dog) 1.0** | (bird) 2.8418578e-12 | (cat) 1.1249883e-12 | (truck) 1.5978992e-21 | (deer) 1.482442e-25 |

**(A) Image of Dog-1 Size 1024*580 pix**

**(B) Image of Dog-2 Size 483*524 pix**




**(C) Image Dog-3 Size 50*48 pix** **(D) Image After Resize inside CNN**

**Figure(4.11):(A), (B), (C) Stage of Resizing,(D) Resize the image to 32×32 pixels in CNN**

## 4.5 Results Comparison

Here, the results of the proposed method with the results of other researches when they applied on the same datasets have been compared.

Smith in (2017) [68] achieved 67% accuracy using Cyclical Learning Rates for training the network by invoking the respective option in Caffe. Renqian Luo et al, in (2018)[61] achieved 65% accuracy. They suggested a simple and an efficient method to automatic neural architecture design based on continuous optimization. They call this new approach as neural architecture optimization (NAO) with taking the description of CNN cell. Pavlo M. Radiuk (2018) [75] used diverse datasets (MNIST and CIFAR-10) and they tried to improve the performance of convolutional neural networks depending on the batch size parameter.They achieved 67% accuracy. In Kshitij Tripathi et al in (2019) [76] hybrid approach of filters or kernel was proposed and was giving better results in comparison to other kernel initializers like variance scaling that normally used in CNN. In their work, they used CIFAR-100 and CIFAR-10 data sets and they achieved 65% accuracy. Enzi Chen et al in (2019) [62] used LeNet-5 convolutional neural network and they achieved an accuracy around 56% . M. Xin and Y. Wang in (2019). [63] based on the analysis of the error backpropagation algorithm, propose an innovative training criterion of depthconvolutional neural network for maximum interval minimum classification error using (CIFAR-10) and (MNIST) dataset, they achieved an accuracy around 83%. D. Roy, P. Panda in (2020) [64] The suggested an adaptive hierarchical network structure composed of DCNNs that can grow and learn as new data becomes available, the network grows in a tree-like fashion to accommodate new classes of data they achieved 86% accuracy. A. S. Winoto et al, in (2020) [65] achieved 93% accuracy using deep convolutional neural network . Investigational results on Cifar-10 dataset illustrate that the multi-convolution neural network is a powerful classifier.

**Table (4.12): Summary of researches on CIFAR-10 dataset**

| Researchers | Year | Dataset | Methods used | Accuracy% |
|---|---|---|---|---|
| L.N.Smith [68] | (2017) | CIFAR-10 | Cyclical Learning Rates for Neural Network | 67% |
| Renqian Luo et al. [61] | (2018) | CIFAR-10 | neural architecture optimization | 56% |
| P.M. Radiuk et al. [75] | (2018) | CIFAR-10 | CNN | 67% |
| K. Tripathi et al. [76] | (2019) | CIFAR-10 | CNN with (Hyper Filter) | 65% |
| Enzhi Chen et al. [62] | (2019) | CIFAR-10 | LeNet-5 convolutional neural network | 77% |
| M. Xin and Y. Wang[63] | (2019) | CIFAR-10 | DCNN | 83% |
| D. Roy, P. Panda [64] | (2020) | CIFAR-10 | DCNN | 86% |
| A. S. Winoto et al [65] | (2020) | CIFAR-10 | DCNN | 93% |
| The proposed approach | (2020) | CIFAR-10 | CNN with Image Mining Techniques | 95% |

In this work, seeked to improve the classification accuracy for a convolutional neural network (CNN) with keras API (Tensorflow backend) which is very intuitive while using one - hot encodeing . also adopt an normalization that to normalize the inputs for the CNN to fit the input range to minimize the error., remove dependence on lighting geometry and The pixels of the images were normalized to the values between 0 and 1.The experimental evaluations confirmed classification accuracies of 95%.

# CHAPTER 5
# Conclusions and Future Works

# Chapter Five
# Conclusions and Future Works

## 5.1 Introduction

This chapter presents the conclusions of the results in addition to the recommendations of the implemented convolution neural network system.

## 5.2 Conclusions

In this thesis, a system for images classification has been designed. After implementing the proposed system, the results have been obtained and the conclusions can be listed as follows:

1. Data pre- Preparation models have high power in classification because these models trained using big datasets and powerful computers and when extracting the data of dataset using normal CNN the accuracy is too high.

2. After selecting the main parameters of architecture for CNN as shown in table (4.1), using the varies batch size for data set makes classifier model has high performance in term of accuracy, number of used parameters and consumed time for training models.

3. Increasing number of fully connected layers andThe number of times of training lead to increasing the delay, without too much affecting the accuracy, in the models in term of training and classifying as explained in section table (4.10).

4. checking all the input images for testing the model, the results showed that all the images were close to the sample of images that the model was trained on. However, still one image (Dog image) that was not recognized by the model. This is due high resolution and massive background in this image. Which leads to losing the main characteristics of the image during the process of resizing in the test phase see table (4.11).

## 5.3 Future Works

There are many points discussed in this thesis which are worth for further investigation. Several suggestions for these future work are given as follows.

1. Classifying another type of data set such as ImageNet, Alex Net, and Google NET.
2. In this thesis, the structure of CNNs is discussed using the Deep Neural Networks architecture. These concepts can be extended to more complex architectures, such as RNNs and DNNs.
3. Currently, it is possible to combine the data set for training using CIFAR-10 and using another data set for testing such as SILF.
4. In the algorithm of the convolutional neural network, we recommended that when using the Cifar-10 database for training , using a technique for segmenting and reducing the size of big images. This is to insert small images for test the model to avoid losing important features of big images when they are resized inside CNN to fit the size of images in the database.

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## الخلاصة

التقدم في تقنيات الحصول على الصور وتخزينها ادى إلى نمو هائل في قواعد بيانات الصور الكبيرة والمفصلةحيث يتم إنشاء كمية هائلة من بيانات الصور مثل صور الأقمار الصناعية والصور الطبية والصور الرقمية كل يوم يمكن لهذه الصور إذا تم تحليلها أن تكشف عن معلومات مفيدة للمستخدمين من البشر. لسوء الحظ ، من الصعب أو حتى المستحيل على الإنسان اكتشاف المعرفة والأنماط الأساسية في الصورة عند التعامل مع مجموعة كبيرة من الصور. يحظى استخراج الصور باهتمام سريع بين الباحثين في مجال استخراج البيانات واسترجاع المعلومات .

تقترح هذه الأطروحة نظامًا لتصنيف الصور حسب واحدة من نماذج التعلم العميق وهي الشبكات العصبية االتلافيفية . الخطوات الأساسية المقترحة في هذه الخوارزمية هي التالية ، الخطوة الأولى هي استخدام قاعده بيانات العالمية "CIFAR-10" ثم اعداد هذه الصورة لدخول الى الشبكة العصبية التلافيفية . الخطوة الثانية هي استخدام نتائج الخطوة الأولى مع طبقة الالتفاف ، ووظيفة Relu ، وطبقة التجميع ، وطبقة التسطيح ، ثم استخدام نتيجة الخطوة الثانية لتصنيف الصورة باستخدام وظيفة الاتصال الكامل ووظيفة softmax.

تم تطبيق النهج المقترح واختبار مجموعات البيانات Cifar 10 باستخدام 60000 صورة مقسمة إلى ثلاث مجموعات 35000 صورة إلى نموذج تدريب , 15000 صورة للتحقق من صحة النموذج و 10000 صورة لاختبار النموذج.