BLOOD CELL SUBTYPE CLASSIFICATION USING CNN

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for the award of the Degree of

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IN

ELECTRONICS AND COMMUNICATION ENGINEERING

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ANIL NEERUKONDA INSTITUTE OF TECHNOLOGY AND SCIENCES
(UGC AUTONOMOUS)

(Permanently Affiliated to AU, Approved by AICTE and Accredited by NBA & NAAC with 'A' Grade)

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CERTIFICATE

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ABSTRACT

Abstract—The Blood and its components have an important place in human life and are the best indicator tool in determining many pathological conditions. There are different machine learning algorithms such as Feature Extraction algorithms (K* classifier, Additive Regression, Decision table)and also different Image Segmentation algorithms such as(Random forest, SVM, and MLR) are discussed and also applied separately to obtain the results. Along these, there is a methodology for the classification of WBC CNN which gives more accuracy. According to the previous methodologies, the MLR performed better than other methods with an average 95% success rate. The proposed methodology (CNN) gives more accuracy and is also able to identify and analyze WBC in a short period. It can be used especially as a source for the diagnosis of diseases.

Keywords—Machine learning, Image Segmentation, Feature Extraction, Convolution Neural Network(CNN), Multinomial Logistic Regression (MLR),Support Vector Machine(SVM),Additive Regression..

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CHAPTER 1

IMAGE PROCESSING

1.1 INTRODUCTION

This chapter describes in detail about what is image processing and types of image representation. It also includes about white blood cell subtypes and what happens if a person suffers from high or low white blood cells and disorders. The detail information about fundamental steps in the processing of digital images also takes part in this chapter.

Image processing can be used to categorise many types of subtypes of white blood cells. Understanding what an image is is crucial before starting any image processing. Based on the quantity of pixels, an image's dimensions (height and breadth) serve as a representation. For instance, 200000 pixels would make up the complete image if it were 500 by 400 (width x height). a group of pixels (image elements) arranged in columns and rows makes up an image. The term "pixel" in image processing refers to this collection of discrete (and typically tiny) cells as an image. An 8-bit greyscale image has an assigned intensity for each picture component that ranges from 0 to 255.

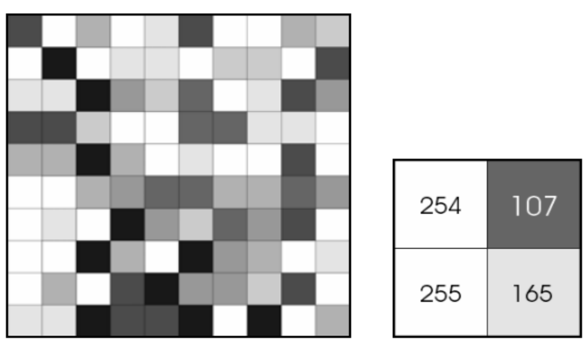

Fig 1.1 Grayscale Image showing pixel value

Each pixel in the image above has worth ranging 0 is black, whereas 255 is white. The colour depth of image determines the potential range of pixel values. Here, each pixel is represented by 256 greyscale tones (8 bits = 256)). Some grayscale graphics include additional levels of grayscale, like 16 bit = 65536.

1.2 PIXEL

Each pixel in a digital image is itself a little rectangle since There is a rectangular grid of pixels dividing the image. Following this, a pixel value that corresponds to each pixel's colour is assigned to it. any difference in colour was before the image was discretized is lost within the pixel because it is presumed that every pixel is the same colour. The picture's discreteness is frequently invisible if the area of each pixel is very small to the human sight.

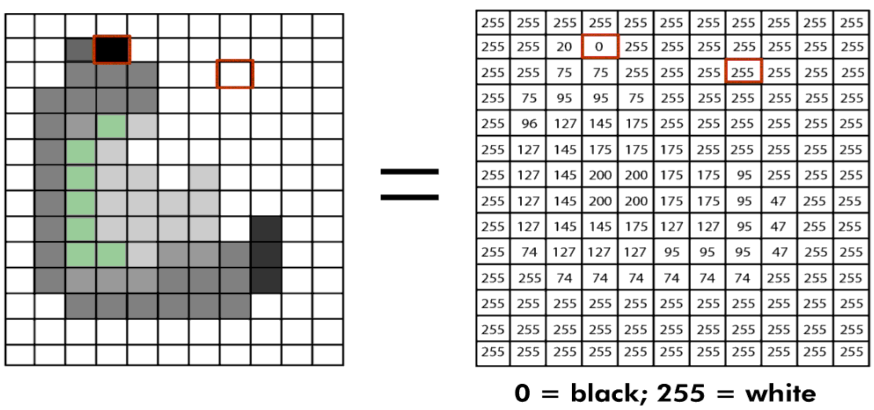

Fig 1.2 Digital Image Representation

The true image is on the left side of the above illustration. The appropriate pixel value for each cell is displayed on the right side.

A pixel value, which describes colour Each of the pixels has a value attached to it. 4comprise an image stored inside of a computer. A grayscale image's pixel value is a single number that represents the brightness of each pixel. White is assumed to be 255 and black is assumed to be a pixel value of zero. Values in the middle make up the various shades of grey.

Image processing involves converting a physical converting an image to a digital format and doing particular operations on it to create a better image or extract additional valuable data from it.

It is a type of signal time where the input can be an image, such as a video frame or image, and the output can be an image or attributes connected to that image. It is one of the technological advancements with one of the fastest growth rates currently due to its use in many different business areas. Graphic design is the cornerstone of research in the domains of engineering and computer science.

The following three phases are the core of image processing.:

- Analysis and image management, such as image enhancement, data compression, and visual pattern recognition using satellite imagery.
- It creates the last phase, when the outcome can be transformed into a picture or report based on image analysis.
- picture processing is a technique that allows someone to improve the quality of a picture or acquire alarming information from an image and feed it to an algorithm to anticipate the future.

1.3 TYPES OF IMAGE PROCESSING

There are three main types in image processing:

- Visualization - Look for objects that are hidden in the picture.
- Sharpening and restoration involve taking the original image and enhancing it by identifying and identifying items in the image.
- This pixel is a location on the image that assumes a certain hue, level of transparency, or colour. Typically, it appears as one of the following.

1.4 TYPES OF IMAGE REPRESENTATION

There are three main types of image representation:

1.4.1 BINARY IMAGE

Black or white are the only two colours that make up a binary picture. A binary image uses 1 bit of memory for each pixel, meaning that 1 bit is used to store the image's data. One or zero represents each of the two colours. A monochrome image is this kind of picture. Binary images are those whose pixel intensities are limited to the integers 0 (which denotes black) and 1 (which denotes white). Usually, these images are used to highlight a distinct area of the coloured picture. It regularly occurs employed, for instance, in image segmentation.

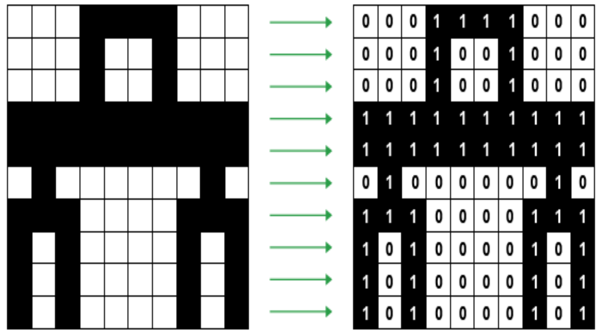

Fig1.3 Binary image

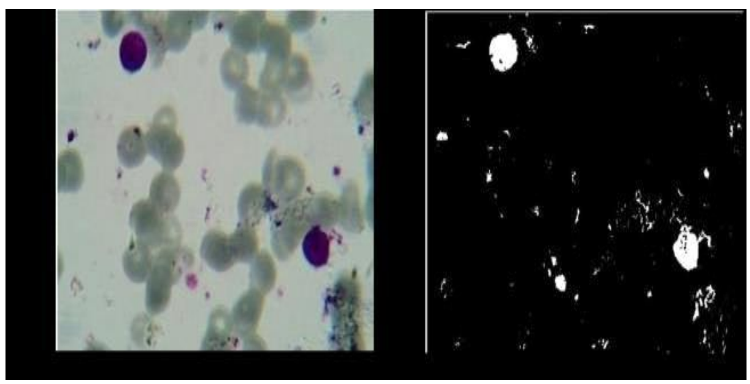

Fig 1.4 Binary image of white blood cells

1.4.2 GRAY IMAGE

Only intensity, or black, white, and various shades of grey, is used in the image. A grayscale image, to put it simply, is one where the only colours are various degrees of grey. Since less information must be provided for each pixel, these images differ from all other types of colour images. Since the red, green, and blue components of an A grey colour are all equal in Only one intensity value needs to be supplied for intensity in RGB space as opposed to the three intensities, one for each pixel required for each pixel in a picture with colour. Grayscale intensity is frequently represented as an 8-bit integer, allowing for 256 distinct shades of grey ranging from black to white. The difference between successive grey levels is substantially better than the grey level resolving power of the human eye provided the levels are regularly spaced.

Because a large portion of today's display and image capture gear can only support 8-bit images, grayscale images are highly prevalent. Additionally, there is no need to employ more complex and challenging to process colour photographs because grayscale images are more than adequate for many applications.

1.4.2.1 Importance of grayscaling :

- Scaling down: For instance, even if grayscale images are one-dimensional, RGB images have three colour three dimensions and channels.

- Reduction in model complexity: Take into account training neural networks on RGB pictures 10x10x3 pixels in size. In the input layer, there will be 300 input nodes. However, the same neural network only needs 100 input nodes for grayscale images.

- For other algorithms to run properly: Many algorithms have been altered to only function on grayscale images. For instance, the Canny edge detection function integrated into the OpenCV library only functions on grayscale photos.

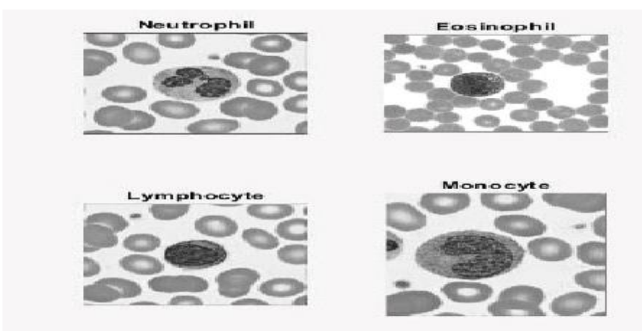

Fig 1.5 Gray scale image of white blood cells

1.4.3 RGB IMAGE

The RGB colour model is an additive a colour scheme that incorporates several combinations of red, green, and blue light a colour scheme that incorporates several combinations of three additive primary colours—red, green, and blue—serve as the inspiration for the model's name.

The RGB colour model is mostly used for sensing. picture electronic gadget display and representation like computers and televisions, however it has also been utilised in traditional photography.

Since different RGB is a device-dependent colour model because colourants (such phosphors or dyes) and how they react to different R, G, and B levels vary from one manufacturer to the next or even over time within the same device. This indicates that various devices will interpret or reproduce a specific RGB value differently. Therefore, an RGB value does not specify the same colour across devices without some type of colour management.

In order to create colourful graphics, we can overlap many 8-bit or 16-bit channels. Red, Green, and Blue are used as the three channels in the well-known RGB image format to determine a pixel's colour.

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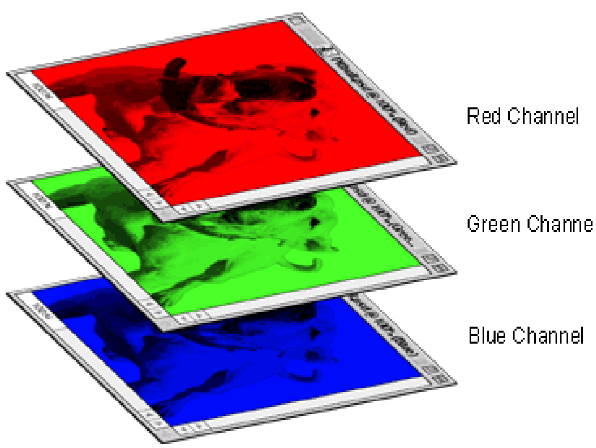


Fig 1.6 RGB Image

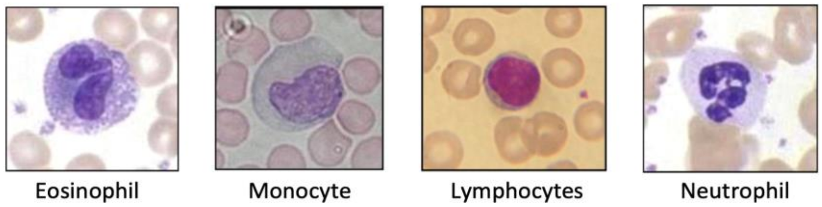


Fig 1.7 RGB Image of white blood cells

1.5 WHITE BLOOD CELLS

A white blood cell is a biological component of the blood that lacks hemoglobin, has a nucleus, can move, and defends the body against disease and infection. It is also known as a leukocyte or white corpuscle. By digesting foreign items and cell waste, eradicating infections and cancer cells, or producing antibodies, white blood cells carry out defence-related tasks. Although some white blood cells are found in the bloodstream, the majority of white blood cells are found in tissues where they fight infections. The tiny number of white blood cells simply circulate from one location to another. As part of a routine physical examination, a doctor may do a blood test to ascertain the white blood cell count (WBC).

To check for or rule out other illnesses that might affect white blood cells, they might order a WBC.

The most common technique to screen for white blood cells is with a blood sample, but a doctor can also look for white blood cells in other body fluids, like cerebrospinal fluid.

A WBC test may be prescribed by a doctor to:

- Check for allergies;
- Check for infections;
- Check for leukaemia;
- Check to see how some disorders are progressing;
- Check to see how well some therapies, like bone marrow transplants, are working.

1.6 NORMAL RANGES

In accordance with an paper in American Family Physician, an average number of white blood cells (per cubic millimetre) at a certain age is as follows:

The following white blood cells are among them::

AGE	NORMAL RANGE
New born infant	13,000 – 38,000
two-week-old baby	5,000 – 20,000
Adult	4,500 – 11,000

If the white blood cells count is high or low then the person suffers from following disorders:

1.6.1 High white blood cell count

The medical word for when the body makes more white blood cells that it ought to is leukocytosis.

The following medical issues may be indicated by a high white blood cell count:

• Those that may induce cell death, such as burns, heart attacks, and trauma; and allergic reactions, such as those brought on by an asthma attack.

• Infections caused by bacteria, viruses, fungi, or parasites; inflammatory disorders such rheumatoid arthritis, inflammatory bowel disease, or vasculitis;

1.6.2 Low white blood cell count

Leukopenia is the term used by doctors to describe when a person's body produces less white blood cells than it should. The following circumstances can result in leukopenia:

• Bone marrow problems; bone marrow destruction, such as through chemotherapy, radiation therapy, or exposure to chemicals; autoimmune diseases like lupus and HIV

• Leukemia

• Lymphoma

• A severe form of infection called sepsis; • vitamin B12 deficiency

1.6.1.1 NEUTROPHILS

The most prevalent form of white blood cell in the human body is the neutrophil, which may be found in blood levels of 2000 to 7500 cells per mm3. Medium- white blood cells are called neutrophils. Have numerous granules and irregular nuclei, which enable them to carry variety of tasks inside the cell.

Function: Neutrophils work by adhering to blood vessel walls and obstructing the entrance of germs that try to enter the blood through a wound or infectious location. Neutrophils are the first cells to reach a spot where a body breach has been established. By "eating" bacteria, a procedure known as phagocytosis, they destroy them. In addition to devouring bacteria one by one, they can also kill a large number of bacteria simultaneously by releasing a burst of super oxides.

1.6.1.2 LYMPHOCYTES

Tiny, spherical large nucleus is encased in a small amount of cytoplasm in lymphocytes. They play a vital part in the humoral immune system, which is an important part of the immune system and is connected to antibody formation. Lymphocytes often settle in lymphatic tissues such the spleen, tonsils, and lymph nodes. There are 1300 to 4000 lymphocytes per mm3 of blood.

Function: B The creation of antibodies by lymphocytes is one of the final stages of disease resistance. A prior infection with a specific pathogen is recalled when B lymphocytes make antibodies, which also create memory cells that are ready to respond whenever the need comes and are ready to prepare pathogens for eradication. The T lymphocyte, which is differentiated in the thymus, is another type of lymphocyte that is essential for cell-mediated immunity.

1.6.1.3 MONOCYTES

The biggest form of white blood cell is called a monocyte. Only 200–800 monocytes may be found in a mm3 of blood. When seen under a microscope, monocytes are agranulocytes, this suggests that they contain fewer granules in the cytoplasm. When monocytes leave the bloodstream, they change into macrophages.

Function: Monocytes carry out the phagocytosis (cell-eating) of any kind of dead cell in the body, including dead somatic cells and dead neutrophils, in their capacity as macrophages. Due to their size, unlike other types of white blood cells, they may digest enormous foreign particles in a wound.

1.6.1.4 EOSINOPHILS

Only roughly eosinophil population in blood ranges from 40 to 400 cells per mm3. They have sizeable granules that help support cellular functions. Eosinophils have a special significance in the context of allergies and worm infestations.

Function: To kill germs, eosinophils expel poisons in their granules. Eosinophils primarily fight parasites and worms as pathogens. High eosinophil levels are associated with allergic reactions.

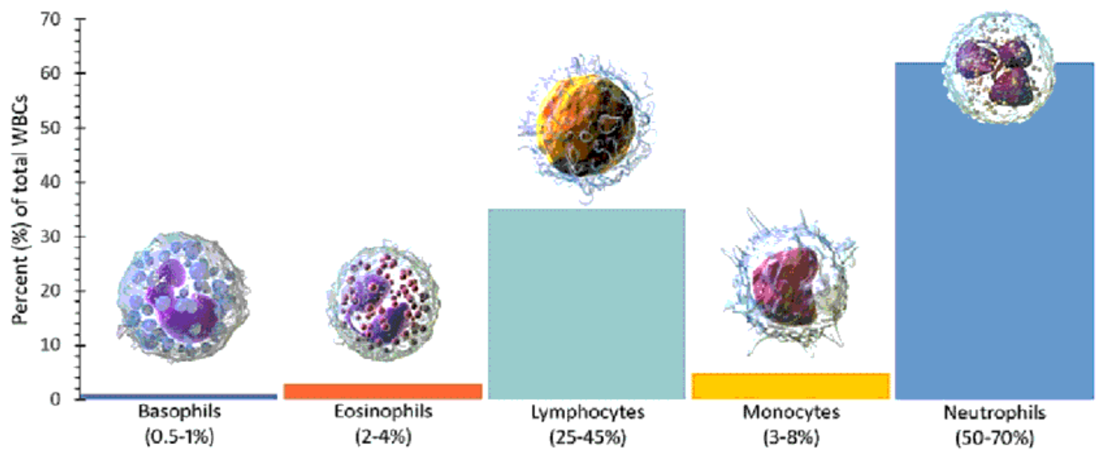


Fig 1.8 White blood cell subtypes

All the white blood cells subtypes like lymphocytes, neutrophils, eosinophils, monocytes which are discussed in detail above undergo the process of fundamental steps of digital image processing and exploit the hidden data of the image and classify them according to there type.

1.7 WHITE CELL FUNCTION DISORDERS

The body's reaction to pathogens and external substances includes white blood cells, or leukocytes. There must be enough white blood cells be alerted to the presence of an an alien or infectious substance in the body, travel to the area where they are most needed, and then kill and digest the threat. White blood cells are created in the bone marrow, just like all other blood cells. Neutrophils, lymphocytes, monocytes, eosinophils, and basophils are the five main types of the white blood cells that they form from stem (precursor) cells during time. Normal daily production of white blood cells is around 100 billion. The term "cells per micro litre of blood" refers to the quantity of white blood cells in a specific volume of blood. Normally, there are between 4,000 and 11,000 white blood cells per micro litre. One may also figure out how many of each of the five main types of white blood cells there are overall in a specific volume of blood.

A problem is indicated by either excessive white blood cell numbers. People are more prone to infections when they have leukopenia, which results in fewer than 4,000 white blood cells per microliter of blood. Leukocytosis, a condition in which there are more than 11,000 white blood cells per microliter of blood, can occur, may be the result of the body's natural response to an infection. However, when the control of white blood cell formation is thrown off, immature or aberrant cells are discharged into the circulation, which can lead to an increase in white blood cells.

Only one of five different types of the white blood cells involved in some white blood cell diseases. Other disorders might involve one or more types, or perhaps all five. The most prevalent conditions are those affecting lymphocytes and neutrophils. Less frequent are abnormalities involving monocytes and eosinophils, and uncommon are those involving basophils. As seen in the following Figure, the blood system also comprises white blood cells in addition to red blood cells, platelets, and plasma.

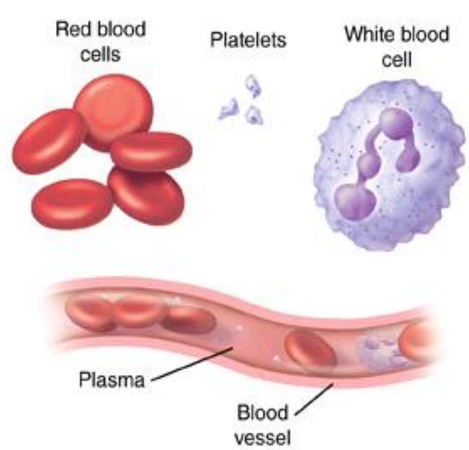


Fig 1.9 Components of the blood system

Despite making only around 1% of the blood, white blood cells have a substantial impact. Leukocytes, also referred to as white blood cells, are essential for health and protection against disease. Consider white blood cells be our immune system's cells. They are, in a way, constantly at war. To combat bacteria, viruses, and the other six foreign invaders that pose a harm to our health, they circulate through our bloodstream. When the body is in danger and a specific area is being targeted, white blood cells rush to the scene to help eradicate the pathogen and prevent illness. Our blood and lymphatic tissues hold the white blood cells that are created in the bone marrow and kept there. Because some white blood cells only live one to three days, our bone marrow is constantly producing them .

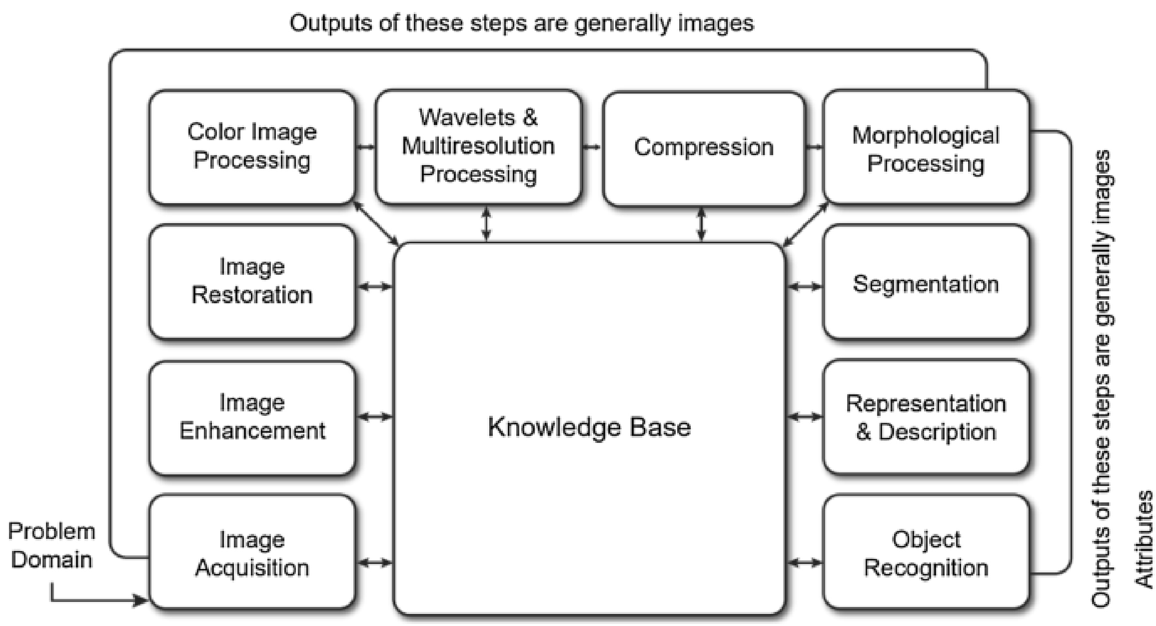
1.8 DIGITAL IMAGE PROCESSING

DIP may be used to enhance a picture taken by a modern camera to our taste. DIP can be used to extract information from images in addition to enhancing image quality. DIP can be carried out on the image using a variety of algorithms.

A digital image is essentially a collection of pixel values. It is an advancement in the processing of data and the understanding of graphical information by humans. Digital image processing facilitates the enhancement of images, rendering them visually pleasing, or in accentuating regions or features of an image for a better representation of the content. An application called digital image processing (DIP) is used to improve raw images from sources such cameras, medical equipment, sensors mounted on satellites and aircraft, surveillance equipment, and common personal gadgets. Sarala, Jacob, and others, [2014]. Astronomy, ultrasonic imaging, remote sensing, medicine, space exploration, surveillance, automated industry inspection, and many other fields are all included in the multidisciplinary field of digital image processing (DIP). The sensor signal is "digitized" and changed into a series of numerical numbers, each of which corresponds to a certain region of the cell's light level. A digital image is stored in computer memory as a collection of the digitised values, often known as "pixels," or elements of a picture. A digital image's standard size is a 512 by 512 array,

where each pixel has value in the range of 0 to 255. The digital image is processed by a computer to achieve the desired result, Rapp C.S.et al., [1996].

1.9 KEY STAGES IN DIGITAL IMAGE PROCESSING



FUNDAMENTAL STEPS IN DIGITAL IMAGE PROCESSING:

1.9.1 IMAGE ACQUISITION:

Image acquisition is the first step in the processing of images. This phase of image processing is frequently referred to as pretreatment. A source must be used to get the image, usually one that is hardware-based.

The goal of the image acquisition process is to capture pictures digitally, such as photographs. Image capture serves the function of transforming optical images (from real data) into a variety of numerical data that can be processed by a computer. Pictures or videos can be acquired as images.

…

1.9.2 IMAGE ENHANCEMENT:

Image enhancement is a technique used to highlight and draw attention to particular intriguing features in a hidden image. This can be achieved by altering the brightness, contrast, etc.

Image enhancement, or raising the quality of an image, is one of the most frequent jobs involved in image processing. It is essential for surveillance, remote sensing, and computer vision jobs. Changing the image's contrast , brightness is a typical strategy.

The brightness difference between an image's lightest and darkest portions is known as contrast. An image's overall brightness can be improved by boosting the contrast, which makes it easier to view. The brightness of an image is its general level of lightness or blackness. Brightness can be increased to make an image brighter and easier to view. Most image editing programmes allow for automated contrast and brightness adjustments as well as manual adjustments.

However, modifying an image's brightness and contrast are simple actions. When upscaled, an image with great contrast and brightness can occasionally become blurry because of the lower pixel density. (pixel density). A new and somewhat more sophisticated idea called "Image Super Resolution" is utilised to overcome this problem, creating high-resolution images from their low-resolution counterparts. To do this, deep learning techniques are frequently employed.

1.9.3 IMAGE RESTORATION:

Image restoration is the process of enhancing an image's look. picture restoration, as opposed to picture augmentation, is carried out utilising specific mathematical or probabilistic models.

Images' quality may deteriorate for a number of reasons, especially if they date from a time before cloud storage was widely used. As an illustration, photos scanned from hard copies made with vintage instant cameras frequently develop scratches.

Image restoration is particularly intriguing since cutting-edge methods in this field might be able to repair damaged old documents. Large portions of lost data from damaged documents may be revealed using potent Deep Learning-based image restoration techniques.

For instance, image inpainting, which is the process of filling in the missing pixels in an image, fits under this category. A texture synthesis method that creates new textures to fill in the missing pixels can be used to do this. However, given to their capacity for pattern identification, Deep Learning-based models are the de facto selection.

1.9.4 COLOR IMAGE PROCESSING

In the processing of coloured images, various digital colour modelling techniques are applied. The importance of this stage has increased as a result of the extensive use of digital photos online. Color image processing entails the evaluation, manipulation, and interpretation of colour-presented visual data. It can produce a range of results, such as the grayscale conversion of a black-and-white image or a careful analysis of the information contained in a telescope image. A variety of applications may be employed, in addition to manual work carried out by programmers, to process digital photos. Both academic institutions and facilities owned by private businesses are actively conducting research and development in this field. When colour pictures are processed, an abstract mathematical model called colour space is used to explain the colours in terms of intensity values. This colour space uses a three-dimensional coordinate system. For varied applications, there are many various colour spaces.

1.9.5 WAVELET AND MULTI RESOLUTION PROCESSING

Images of varying resolutions are represented by wavelets. For the purposes of pyramidal representation and data compression, the images are separated into wavelets or smaller sections. A wavelet is a mathematical function used in digital signal processing and image compression. It can be isolated in terms of frequency/wavenumber, time/spatial position, and basis function. Images that have been compressed using wavelet technology are smaller than JPEG images and can be downloaded and transferred more quickly across networks. Wavelet technology is employed in the compression of images, signals, and videos.

1.9.6 WAVELET PROPERTIES:

- Two crucial characteristics are admissibility and regularity.
- Admissibility:

Stated as $dw < \infty$ Eq 1.1

where $\psi(t)$ is a wave in the time domain, and $\Psi(\omega)$ is the Fourier transform $\psi(t)$

In practice, $\Psi(\omega)$ will always have sufficient decay so that the admissibility criterion reduces to the requirement that $\Psi(0) = 0$, or Regularity

- Put in place to make sure the wavelet transform drops off fast as scale goes down.
- Another requirement of this is that the wavelet function be smooth and concentrated in both the time and frequency domains. - Admissibility and regularity combine to generate the wave and let elements of the wavelet, respectively.
- Let denotes rapid decay.

1.9.7 COMPRESSION:

Image compression is the process of shrinking an image's file size while attempting to maintain the image's quality. This is done to conserve storage space, especially when using mobile and edge devices to conduct image processing algorithms, or to lower the bandwidth needed to send the image.

Conventional methods employ lossy compression algorithms, which work by slightly lowering the image quality in order to reduce the file size. For instance, the Discrete Cosine Transform is used by the JPEG file format to compress images.

Modern methods of image compression use Deep Learning to encode images into a smaller feature space, which is subsequently recovered by a decoding network on the receiving end. These models are referred to as autoencoders, and they are made up of an encoding branch that learns a useful encoding scheme and a decoding branch that aims to recover the picture loss-free from the features.

1.9.8 MORPHOLOGICAL PROCESSING:

An assortment of processing techniques known as "morphological processing" are used to change the shape of photographs.

The morphology or shape of features in an image is a topic that is addressed by all of the non-linear techniques used in morphological image processing. Given that morphological processes only take into account the relative ordering of pixel values rather than their numerical values, binary image processing is particularly well suited for these applications. Standard methods employ lossy compression algorithms, which reduce image quality significantly in order to reduce file size. For instance, the Discrete Cosine Transform is used to compress images in the JPEG file format.

1.9.9 SEGMENTATION:

The division of a picture into various segments or regions is known as image segmentation. Image segmentation is frequently used as preprocessing step for object detection. Each segment represents a different object in the image.

Segmentation is one of the most difficult components of image processing. It involves breaking down an image into its various objects or elements. Thresholding is one of the most often used approaches for segmenting images, despite the fact that there are many different algorithms that can be used. For instance, when using binary thresholding, an image is converted into a binary image where each pixel is either black or white. The threshold value is chosen to convert all pixels to black and white, accordingly, depending on whether their brightness levels are below or over the threshold. As a result, since each object is now represented by a distinct black and white zone, the image's objects are segmented.

1.9.10 REPRESENTATION AND DESCRIPTION:

A picture is divided into sections during the segmentation process, and each section is then represented and described in a way that is appropriate for future computer processing. Through representation, the quality and regional components of the image are covered. The task of description is to gather quantitative information that aids in differentiating one class of goods from another.

1.9.11 RECOGNITION:

An object receives a label by recognition using its description. Image recognition refers to technologies that can identify landmarks, company logos, people, objects, buildings, and other details in digital photographs. Many visuals, such as images of animals, may be relatively straightforward for humans like you and me to recognise. The image of a cat is easy to recognise and distinguish from the image of a horse. However, a computer might find it more challenging.

The picture elements, also known as pixels, that make up a digital image each have a specific, finite quantity of numeric representation for their level of intensity. The computer interprets an image as a collection of numerical values for these pixels, and in order to identify a particular image, it must find patterns and regularities in this numerical data.

1.10 BENEFITS OF IMAGE PROCESSING:

- • The employment of methods for image processing has had a substantial influence on several IT companies. The ones that follow represent a few of the most beneficial benefits of image processing, regardless of the business:

- • Because the digital picture may be made available in any format that is required (more favourable image, X-Ray, picture negative, etc.), it allows for to further enhance images for human interpretation.

- photographs may be processed and information extracted for machine interpretation, and the pixels can be adjusted to any desired density and contrast. Images can also be stored and retrieved with ease, and it is possible to send photographs electronically to third-party providers quickly.

1.11 ADVANTAGES OF IMAGE PROCESSING

Processing of images happens more rapidly and effectively. There is a reduction in the amount of film, other photographic equipment, and processing time. It is more environmentally friendly to process images. Without using any fixing or processing chemicals, digital photos can be taken and edited. However, printing inks are essential when printing digital photos. The quality of a digital photo can be seen right away after it is taken. Unless it is compressed, a digital image can be easily copied while maintaining its quality. For instance, when an image is saved in jpg format, it gets compressed. The quality of the image degrades with each save because each time you save an image in jpg format, the previously compressed image must be recompressed. Image correction and retouching have gotten simpler.

1.12 DISADVANTAGES OF IMAGE PROCESSING

Copyright infringement is now simpler than it formerly was. For instance, photographs on the internet can be duplicated with just a few mouse clicks. Despite the fact that downloading photographs from the internet is quick and simple, the worth of the image will decline. Old careers disappear, and new ones don't always emerge. After a certain size, a digital file can no longer be enlarged in excellent quality.

1.13 APPLICATIONS OF IMAGE PROCESSING

Visual information is the most important type of information that the human brain observes, analyzes, and interprets. Digital image processing, a computer-based technology, automatically analyses, modifies, and interprets this visual input. It is used in a variety of scientific and technical fields, including as robotics, imaging, watching television, mapping, medical diagnosis, and corporate inspection, and it is becoming more and more important in many aspects of our everyday lives.

CHAPTER 2

LITERATURE SURVEY

White blood cells are classified using many Machine Learning algorithms and using Convolution Neural Networks. But some machine learning algorithms follow Feature Extraction Technique and some follow the Image Segmentation Technique. According to the survey in feature extraction algorithms the Multinomial Logistic Regression have the highest accuracy and in image segmentation algorithms the K* classifier have the highest accuracy. We undergo the process of deep learning which replaces with convolution neural network and classify the subtype in shorter period of time with highest accuracy.

2.1 Feature Extraction

A technique used in image processing to decrease the quantity of data displayed is called feature extraction. The process of converting input data into a property dataset is called feature extraction. Feature extraction algorithms scan objects and images to extract the most distinctive traits that reflect various object types. The class to which they are assigned is represented by the property vectors, which are used as input parameters by the classifiers. The goal of feature extraction is to scale particular qualities or properties that separate one input set from another set in order to decrease the original data. The selection of the attributes has an impact on how well the classifiers work, and feature extraction is a crucial step in the automatic classification of the white blood cells. The classification's accuracy dependent on number of features, and feature properties.

Machine learning algorithms that follows Feature Extraction:

- **Support Vector Machine (SVM)**
- **Random Forest**
- **Multinomial Logistic Regression(MLR)**

2.1.1 Support Vector Machine (SVM)

Structured risk minimization and convex optimisation are the foundations of a machine learning system known as the Support Vector Machine. It is primarily used to overcome problems with binary categorization. To best separate the classes from one another, a hyperplane should be made. Typically, class names like "-1" or "+1" are used in the classification to express it. The data that needs to be classified might not be possible to be divided by a single line or might not be able to be linearly separated (AND/OR difficulty). (XOR issue). As a result, based on the data, SVM is divided into Linear SVM and Nonlinear SVM groups. Classification issues in the actual world generally involve a maximum of two classes, as is widely recognised. It is necessary to use a multi-class classifier based on SVM to address such problems. Combining binary classifiers can produce multiple classification. The decision function of the ideal separating planes will be as in Equation (2.1) if it is believed that the train data consist of n amount of samples for training of SVM in a linear separable class classification issue is x, y, 1, +1, ?

$$y_i = \begin{cases} w.xi + b \geq +1, +1 \\ w.xi + b \geq -1, -1 \end{cases} \qquad \text{Eq 2.1}$$

Where represents the labels where the inputs are categorised as "-1, +1" and represents the D-dimensional space of the input patterns. reflects the tendency (bias) value, which is the multiple plane's normal value. The boundaries parallel to this correction must be identified in order to identify the best distinct ion plane. In other words, support vectors are necessary. The formula for this step is w. x+b=+1. Many additional image processing issues do not allow for linear data separation, just like when classifying medical images. In this instance, the issue can be resolved by creating a positive artificial variable and placing a portion of the training data on the opposite side of the ideal hyperplane. One way to manage the balance between increasing the boundary value and reducing misclassification errors is to find the edit parameter denoted by that only accepts positive values.Equation describes the optimisation problem for data that cannot be linearly differentiated using the regulation parameter and the fake variable. (2.2).

$$\text{Min}[\ 1/2\ ||w||^2 + C\sum \varepsilon i\ r\ i{=}1\ ] \qquad \text{Eq 2.2}$$

Mathematical expressions are used to express this's limitations. The data that cannot be separated linearly in the input space is shown in a multidimensional space known as the property space[10] in order to solve the optimisation challenge posed by Equation above.As a result, it is possible to create a linear separation between data and establish the hyperplane between classes. An algebraically stated kernel function can be used to create nonlinear transformations. As a result, Equation 2.3 below can be used to represent the decision rule for the resolution of a two-class problem that cannot be linearly separated using the kernel function.

$$f(x) = \text{sign}\left(\sum_{i=1}^{k} \alpha_I y_i \Psi(x)\, \Psi(x_i) + b\right) \qquad \text{Eq 2.3}$$

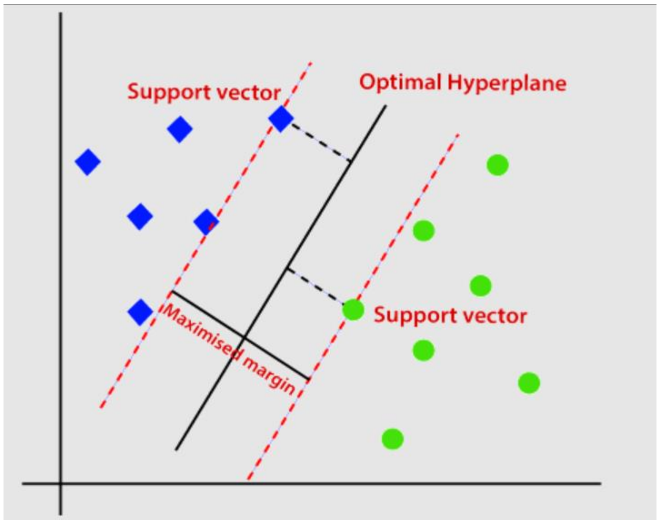


Fig 2.1 Support Vector Machine

2.1.2 Random Forest

Breiman created the Random Forest method in 2001. Instead of creating a single decision tree, this method combines the judgements of numerous multivariate trees, each of which was trained using a distinct set of training data. As a result, it is an algorithm that solves classification issues with a high degree of success. As with other decision tree approaches, choosing an appropriate pruning procedure and deciding on branching criteria are crucial in the Random Forest algorithm. The most used gain measurement methods for establishing the branching criteria are gain ratio and Gini index. The number of trees to be created and the amount of samples used for each node are the two different parameters that govern how this algorithm operates. The user-defined tree is mostly formed during the classification phase. When a new sample needs to be classified, the decision tree is used to process it, and the class of the new sample is chosen based on the highest rate discovered by these trees.

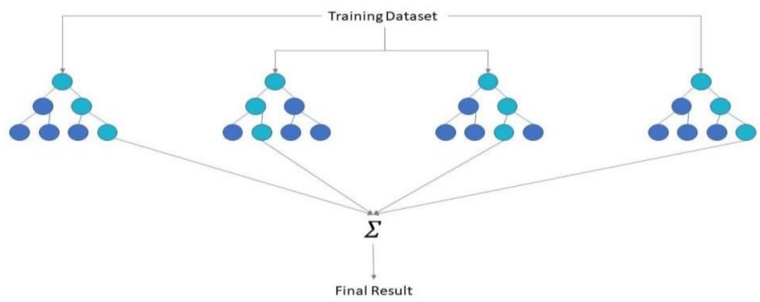


Fig 2.2 Random Forest

2.1.3 Multinomial Logistic Regression (MLR)

Using the cause-and-effect relationship between two or more variables, regression analysis is a statistical approach used to estimate or predict a subject. Logistic regression (LR) is a nonlinear regression model with two dependent variables. MLR is used to describe the cause-and-effect correlations between the dependent variable and the independent variables when the dependent variable has at least three categories and the values are decided by a classification scale.Since the objective of the study is to estimate the value of categorically dependent variables, this is an estimate of membership for two or more categories. As a result, the approach's objectives include classifying data and investigating the relationships between dependent and independent variables. The LR model, which is represented as Equation below, is a particular kind of generic linear model found for dependent variables having a binomial distribution. $\pi(x) = \alpha+\beta 1x1+\beta 2x2+\cdots+\beta pxp$ $1+e\ \alpha+\beta 1x1+\beta 2x2+\cdots.+\beta pxp$. Here, the independent variables regression coefficients, x1, x2,..., arguments, independent variable number, and error term represent the probability of an occurrence under investigation. According to the equation below, the MLR model is an expanded version of the LR model with two states.

$\pi j\ (\ ) = e\ \alpha+\beta 1x1+\beta 2x2+\cdots+\beta pxp\ 1+\sum e\ \alpha i+\beta 1j\ x1i+\beta 2j\ x2i+\cdots+\beta pj\ k-1\ xp\ j=1$ Eq 2.4

Here, j1,j2, … ,represents category, (i1, i2, … ,) represents the level of possible

independent levels.

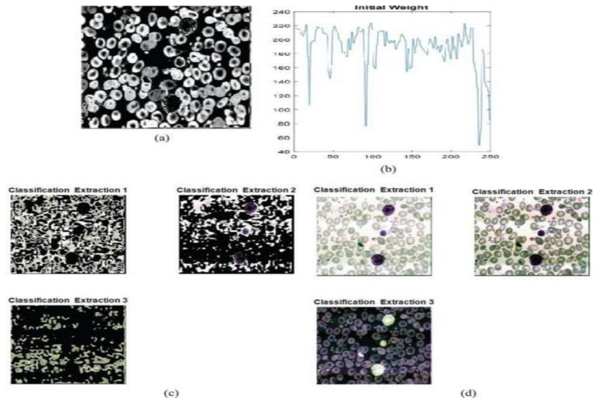


Fig 2.3   Visualization Of Different Levels Of Extraction

FEATURE EXTRACTION				
ALGORITHM	**ACCURACY**	**MEAN**	**STD.DEV**	**MEDIAN**
MULTINOMIAL LOGISTIC REGRESSION	96.5	91.26	2.73	91.95
SUPPORT VECTOR MACHINE (SVM)	84.4	74.78	3.62	75
RANDOM FOREST	91.3	78.94	3.99	79.31

Table 2.1 Feature Extraction summary

2.2 IMAGE SEGMENTATION

The background of the image that contains RBCs, platelets, and other objects must be removed in order to segment the cells. The segmentation process results in the growth of white blood cells, the objects of powers. The nucleus and cytoplasm of a white blood cell should be included after accurate segmentation. Some of the characteristics that are thought to be necessary for classifying a cell are its shape, size, texture, and amount of substance.

The most important phase in image processing is image segmentation, which has a direct impact on subsequent processing. According to scientific ideas, picture segmentation has advanced quite well, and numerous cutting-edge segmenting algorithms have been introduced. Even the most effective techniques contain flaws. It still presents a difficult challenge to distinguish and count cell pictures because of how complex the universe is.

Machine learning algorithms that follows image segmentation technique:

- **K-Star Classification Algorithm**
- **Decision Table**
- **Additive Regression.**

2.2.1 K* CLASSIFICATION ALGORITHM

A classifier that uses an instance-based methodology is called K-star or K*. Using a correlation function, this technique tries to determine whether the instance is connected to any of the training dataset. This approach differs from other instance-based learners because it makes use of a function known as the entropy-based function. By putting the circumstance into the set of data that corresponds to the pre-defined and categorised models, this function categorises the situation. The crucial aspect of this idea is that related situations are bestowed with related categorization. The k-nearest neighbours algorithm, sometimes referred to as KNN or k-NN, is a classifier based on supervised learning that uses proximity to create predictions or categorizations about how a single data point would cluster. It may be used to tackle classification or regression issues, but because it is based on the idea that adjacent comparable points can be located, it is commonly employed as a classification tool.

2.2.1.1 EUCLEDIAN DISTANCE:

$$d(p,q) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \qquad \text{Eq 2.5}$$

$$d(p,q) = \sqrt{(p_i - q_i)^2 + (p_2 - q_2)^2 + (p_3 - q_3)^2} \qquad \text{Eq 2.6}$$

2.2.1.2 MANHATANN DISTANCE:

$$\text{distance} = \sum_{i=1}^{n}|x_i - y_i| \qquad \text{Eq 2.7}$$

2.2.1.3 MINKOWSKI DISTANCE:

$$D(X_i, X_j) = \left(\sum_{i=1}^{d}|x_{il} - x_{jl}|^{\frac{1}{p}}\right)^{p} \qquad \text{Eq 2.8}$$

2.2.1.4 HAMMING DISTANCE:

$$D_H = \sum_{i=1}^{k} |x_i - y_i| \qquad \text{Eq 2.9}$$

$$x=y \Longrightarrow D=0$$

$$x \neq y \Longrightarrow D=1$$

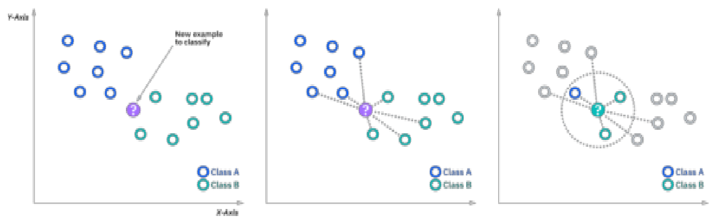


Fig 2.4 K-Star Classification

2.2.2 DECESION TABLE ALGORITHM

A Decision Table is a tool used to generate a complete set of test cases without using the programme in question's built-in design. We use a table to store the input and output values of a programme in order to create test instances. This table is broken into four sections. (Stub portions, Actions, Entry portions, and Conditions). The decision tree algorithm is a supervised machine learning technique that continuously splits data at each row based on specified criteria until the desired outcome is obtained.

The decision tree or table uses a variety of strategies, including:

- Splitting is the process of dividing data sets into smaller groups.
- Pruning is the process of shortening the decision tree's branches to reduce the depth of the tree.
- Pre-pruning - In this method, the tree is stopped growing when there is no statistically significant correlation between the attributes and class at any given node.

- Post-Pruning – Before cutting the branches caused by overfitting noises from the training set, we must first assess the efficacy of the experimental set model.

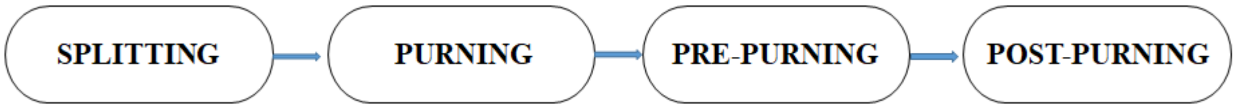


Fig 2.5 Decision Table

2.2.3 ADDITIVE REGRESION ALGORITHM

A meta classifier that makes a regression base classifier look better. Every repetition gives the residuals the classifier created on the previous iteration a pattern. By including the forecasts from any reliable classifier, the forecast is produced. Limit overfitting is supported and has a smoothing effect when the reduction (learning rate) parameter is overcome, but it also improves the learning process. Similar to how linear regression can be used for classification, additive regression can as well. However, we are aware that logistic regression is better suited for the classification than linear regression. It turns out that additive models can also be adjusted in a similar way by changing the forward stagewise modelling method to perform additive logistic regression. Use the logit transform to turn the probability estimation problem into a regression problem. Assume that fj(a) is the ensemble's forecast for example a and that fj is the ensemble's jth regression model. If there are two classes, use the additive model fj(a) to estimate the probability for the first class.

$$P(1|a) = \frac{1}{1 + e^{-\Sigma f_j(a)}} \qquad \text{Eq 2.10}$$

In this case, yi is 1 for a first-class instance and 0 for a second-class instance. This algorithm uses weights wi and dummy class values zi to fit a regression model fj to a weighted version of the original dataset in each iteration. We suppose that the fj created in earlier iterations are used to compute p(1|a).

K* classifier was more accurate than other machine learning techniques in this case. The classification of white blood cells is based on these machine learning methods. Now that we know that deep learning is effective at processing images and that it also produces results that are more accurate than machine learning algorithms, machine learning is good with numbers.

IMAGE SEGMENTATION				
ALGORITHM	**ACCURACY**	**CORRELATION-COEFFICIENT**	**MEAN ERROR**	**REAL-TIVE ERROR**
DECISION TABLE	92.2	0.9874	0.06	0.50
ADDITIVE REGERSSION	89.4	0.9316	0.4578	0.38
K* Classifier	94.3	1	0	0

Table 2.2 Image Segementation summary

Therefore, we draw the conclusion that feature extraction and picture segmentation techniques are used to classify the blood cell subtypes. However, with the advancement of the internet and image processing, deep learning is currently used to classify unknown images according to their subtype with the maximum level of accuracy and substitutes CNN. According to a literature review, the K*classifier and MLR have the highest accuracy rates among all currently used algorithms in terms of image segmentation and feature extraction, respectively, with 94.3% and 96.5%, respectively.

CHAPTER 3

DEEP LEARNING

3.1 INTRODUCTION

The popularity of deep learning methods that use deep neural networks has grown as high-performance computing resources have proliferated. When working with unstructured data, deep learning achieves greater power and flexibility because it can handle an extensive amount of features. The data is passed through several layers of the deep learning algorithm; each layer has the ability of gradually extracting features and passing the data to the layer which was next. Following layer combine low level features to create a complete representation, while the beginning layers extract low-level characteristics. In Section 2, a summary of the creation of models based on deep learning is given. Section 3 provides a quick overview of all the different learning approaches, such as supervised learning, unsupervised learning, and hybrid learning. Data with labels is used in supervised learning for training the network of neurons. Using unlabeled data, the network learns recurring patterns through supervised learning. In order to achieve better results, hybrid learning mixes supervised and unsupervised methods. Convolutional neural networks, recurrent neural networks, recursive neural networks, and unsupervised pre-trained networks are a few examples of the various architectures that can be used to implement deep learning and are discussed in section 4. The training methods and optimisation techniques introduced in Section 5 help to produce better results. In Section 6, we cover the structures that let us develop tools that offer a better working environment. Despite the numerous difficulties in deep learning applications, A quick summary of several exciting applications that have the potential to revolutionise society is given in Section 7.

3.2 DEVELOPMENT IN DEEP LEARNING

The initial creation of artificially neural networks (ANN), that had an infinite amount of calculations, consisted of perceptrons in neural layers. The second generation calculated and propagated the error rate. The prohibited Boltzmann machine getover the restriction of backpropagation and make learning easy. Eventually, other networks evolve [15,24]. A chronology of development of deep learning model and the conventional models is shown in Figure 1.

Deep neural network classification algorithms execute considerably better with more information when contrasted with conventional approaches to learning. Figure.2 compares the performance of deep learning with traditional machine learning techniques [6].

Traditional machine learning algorithms' performance stabilises once they reach a certain size of the training data, whereas the performance of deep learning algorithms improves as the amount of data increases. Deep learning is now employed in wide range of applications, including chatbots, automatic email and text answers, The suggestion systems on Netflix and Amazon, Siri on Apple devices, and Google's recognition of speech and images.

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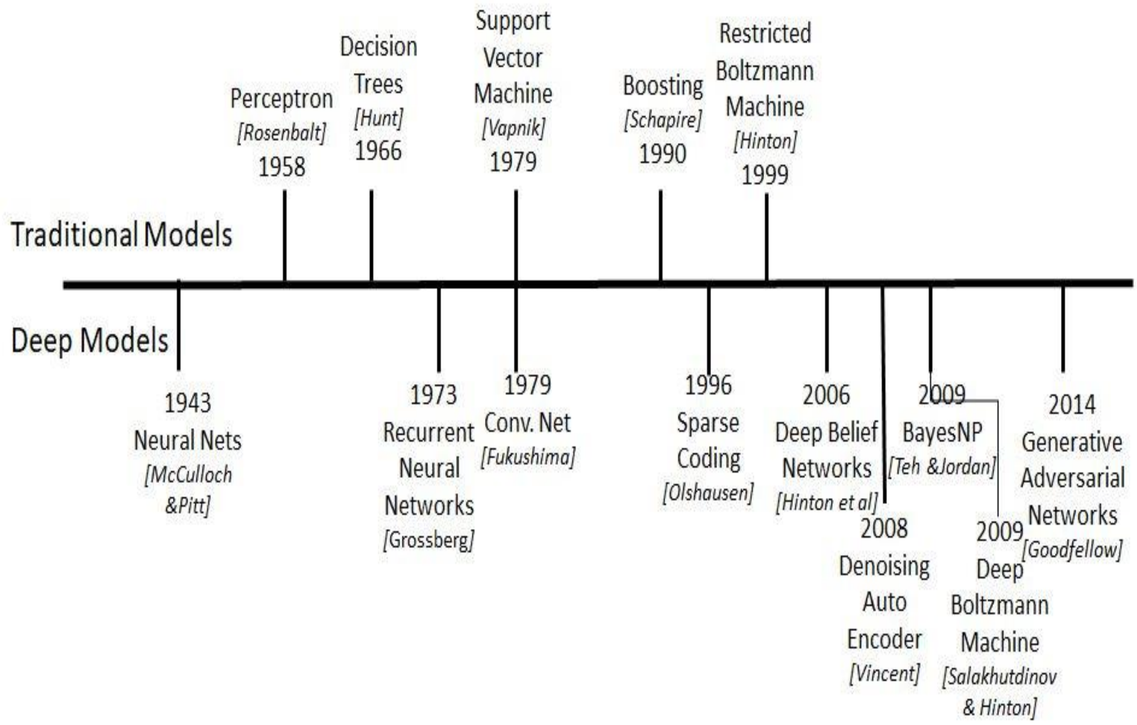


Fig 3.1 Evolution of Deep Models

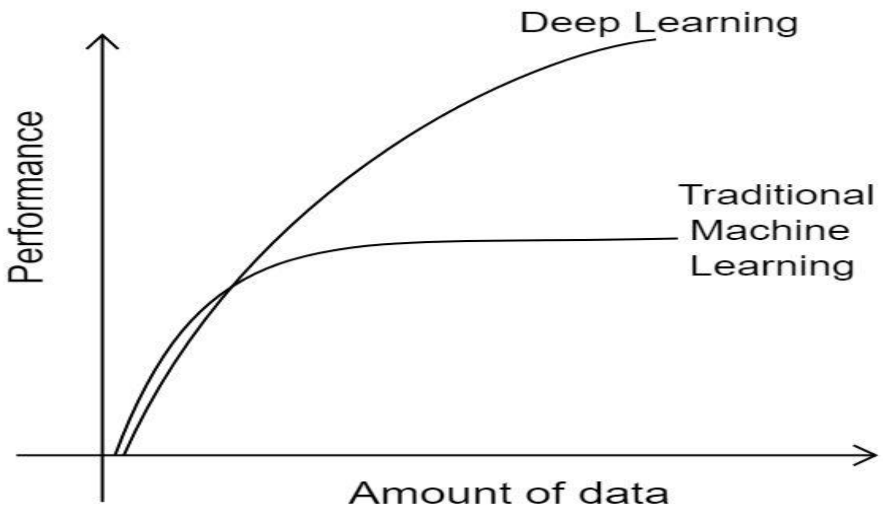


Fig 3.2 Why Deep Learning?

3.3 DEEP LEARNING APPROCHES

Reward learning, supervised learning, unsupervised learning, and hybrid learning are all possible with deep neural networks.

3.3.1 SUPERVISED LEARNING

In the context of supervised learning, an approach is used to acquire a mapping function f, which maps variables that are input reflected as the X to the output factors symbolized as Y.

$$Y = f(X) \qquad \text{Eq 3.1}$$

The goal of the method of learning is to get the results (Y) for an unknown inputs by roughly representing the mapping function. (X). The result can be corrected using the forecasting error that was produced during training. Learning can be stopped once all of the components have been trained to generate the outcome you want. SVMs are employed for classification, regression problems are solved using regression, and issues with classification and regression are both solved using Random Forest.

3.3.2 UNSUPERVISED LEARNING

We have just input data and no related output to map in learning without supervision. By simulating the distribution in the data, this educational process aims at acquiring knowledge about data. Algorithms are capable of spotting the intriguing structure that exists in the data. To resolve connectivity and clustering problems, unsupervised learning is applied.

Unsupervised learning techniques including the K-means algorithm [9] are used to handle clustering difficulties, and the Apriori algorithm is used to address association problems.

3.3.3 REINFORCEMENT LEARNING

Reinforcement learning, which uses an arrangement of incentives and repercussions, is used to train the algorithm. In this, a computer program or agent gathers data about its surroundings. An agent is rewarded for good performance; when they perform poorly, they are punished. Consider a self-driving car as an illustration; the agent is rewarded for arriving at the intended location safely and penalised for veering off the road. A programme for playing chess might have an incentive state of prevailing and an adverse state of being checked similar to this. The agent tries to make the reward greater and the punishment less severe. The algorithm resolves the problem on its own in reinforcement learning; it doesn't get instructions on how it is to carry out the learning process.

3.3.4 HYBRID LEARNING

An architecture for learning that combines prejudiced (supervised) and productive (unsupervised) elements is called a hybrid architecture. By combining several designs, a hybrid neural network with deep learning may be created. They are anticipated to deliver substantially superior outcomes and utilise step banking traits to recognise human movements.

3.4 ESSENTIAL DEEP LEARNING ARCHITECTURES

Although neural network structures take longer to train than ANNs, their results are better than them overall. However, the training period may be shortened by utilising strategies such as transfer instruction and GPU computing. The meticulous network's design is one of the elements that determines whether neural networks are financially successful. Below is a discussion of a few of the pertinent neural network topologies.

3.4.1 UNSUPERVISED PRE-TRAINED NETWORK

Unsupervised computing pre-training is developing a model independently before using it to make predictions. In the section that follows, a few unsupervised pre-training architecture are covered.

Autoencoders: These are utilized for things like data reduction in dimensions, novelty identification, and identifying anomalies. The first layer of an autoencoder is built as an encode layer, and the second layer is built as a decoder. Use the unsupervised approach to train it to duplicate what you provide after that. After training, adjust the layer's weights. Continue to the following layer once the previous layers of the deeper net have all been successfully trained. After that, we back to the classification/regression issue we attempted to resolve with deep learning and use stochastic gradient descent to optimize it, employing the parameters acquired through pre-training.

A system of autoencoders has two components. The encoding process converts the input into the latent space democracy, which is shown by:

$$h = f(x) \qquad \text{Eq 3.2}$$

The decoder reconstructs the input using the latent space representation, which is represented as:

$$r = g(h) \qquad \text{Eq 3.3}$$

Autoencoders can be conceptualised as equations. The decoding output, r, will resemble the input x.

$$g(f(x)) = r \qquad \text{Eq 3.4}$$

3.4.1.1 DEEP BELIEF NETWORKS

Skills for learning The first stage in profound neural training for networks is to use the first layer. Activate trained qualities and use them in the following layer. Continue doing this all the way to the top layer. Restricted Boltzmann Machines categorisation(RBM) are used to train each layer of deeper beliefs network (DBN), and a network of feed-forwards is used to make any final changes. DBN learns concealed patterns globally as opposed to other deep nets where every single layer gradually picks up complicated patterns.

3.4.1.2 GENERATIVE ADVERSARIAL NETWORK

Ian Goodfellow discussed generative adversarial networks (GAN). The generator network and the discriminator networks are its constituent parts. The discriminator verifies the content once it has been prepared by the generator. The generator creates images that appear natural while the discriminator assesses whether a picture looks that way. A two-player minimax approach is known as GAN. categorisation-forward and convolutional neural networks, respectively, are used by GANs.

3.4.2 CONVOLUTIONAL NEURAL NETWORKS

Images are major application for convolutional neural networks (CNN). By giving each thing in the image an alternate weight and bias, it separates various items in the picture. It needs less pre-processing compared to other classification techniques. CNN uses the appropriate filters to capture the temporal and spatial relationships that exist in an image [12,25]. Among the many CNN architectures are LeNet, which is Alex Net, the VGG Net, Google Net, Res Net, and ZF Net. CNNs are mostly employed in the areas of object detection, semantic segmentation, and captioning.

3.4.3 RECURRENT NEURAL NETWORKS

In recurrent neural networks (RNN), the results of the earlier states are fed into the present state. The buried layers of an RNN can retain data. The hidden state is modified using the results of the stage's output. RNNs may be utilized for forecasting time-series data since they have something is known as categorisation-Short Term Memory, also known as which enables them to keep previous data points in addition.

3.5 DEEP LEARNING METHODS

The strategies for reducing time spent training and enhancing modeling that can be utilised using deep learning algorithms are covered in the following part. Benefits and downsides for each approach are listed in Table 1.

3.5.1 BACK PROPOGATION

Back-propagation is able to be utilized to determine the gradients of the function in question for each iteration of an optimisation problem when employing a gradient-based method to solve the issue.

3.5.2 STOCHASTIC GRADIENT DESCENT

Methods for gradient descent that use the convex function ensure that the ideal lowest is reached without getting stuck at a local minimum. Based on the categorisation's variables, training rate, and step size, it may approach the optimum value in different ways with different speeds.

3.5.3 LEARNING RATE DECAY

When the algorithm's learning rate is altered, stochastic gradient descent algorithms perform more efficiently and need a shorter training time. During the training process, gradually lowering your comprehension rate is the approach that is most usually used. This makes it possible to start out with big improvement. This makes it possible to modify the weights further.

3.5.4 DROPOUT

The drop out approach can be used to tackle the overfitting issue in deep neural networks. This method includes randomly eliminating unit and interconnections during training. Dropout provides an effective regularisation method that reduces overfitting and increases generalisation error. Dropout offers a better learning on supervised learning tasks into visual computing, biological computation, document categorization, and recognition of speech.

3.5.5 MAX POOLING

In max-pooling, a predetermined filter is applied to the input's nonoverlapping subregions, and the output of the filter is the highest value in the window. Max pooling may be used to lessen complexity and the cost of computing required to learn several parameters.

3.5.6 BATCH NORMALIZATION

Batch normalisation accelerates deep learning because it reduces covariate shift. The data provided to the layers for every mini-batch are normalised when weights are modified during training. Training epochs are cut down while learning is stabilised by normalisation. To improve a neural network's stability, the result of the preceding activation layer can be normalised.

3.5.7 SKIP-GRAM

Word embedding techniques can be modelled using Skip-gram. The skip-gram model describes two vocab words which are similar in contexts and then identical. "The cats are animals" and "dogs are mammals" are two examples of acceptable sentences that have the identical sense as "are mammals." By taking into consideration a context frame with n phrases, learning a network of neural networks by omitting a single of them, and finally utilizing the model to predict the missed term, a skip-gram can be implemented.

3.5.8 TRANSFER LEARNING

In transfer learning, an algorithm that has been learned for a single assignment is applied to a related task. The knowledge acquired while tackling a given problem can help a different network who will be taught on a related topic. This allows for a quicker and more effective solution to the second issue.

S.NO	Deep Learning	Machine Learning
1.	To be qualified for deep learning, there has to be at least three layers	Can be defined as a shallow neural network which consists one input and one output, with barely one hidden layer
2.	Requires large amount of unlabelled training data	Requires small amount of data
3.	Performs automatic feature extraction without the need for human intervention	Cannot perform automatic feature extraction, requires labelled parameters
4.	High-performance hardware is required	High-performance hardware is not required
5.	Can create new features	Needs accurately identified features by human intervention
6.	Offers end-to-end problem solution	Tasks are divided into small portions and then forms a combined effect
7.	Takes a lot of time to train	Takes less time to train

Table 3.1 Comparison of Deep learning and machine learning

3.6 DEEP LEARNING FRAMEWORKS

Without getting into the specifics of the underlying algorithms, the deep learning frameworks aids more quickly modelling a networks. Every framework is designed differently for every function. Below are some deep learning frameworks that are also listed in Table 3.2.

3.6.1 TENSOR FLOW:

Google Brain's TensorFlow supports languages including Python, C++, and R. It enables us to use both CPUs and GPUs for our deep learning models.

3.6.2 KERAS:

An API called Keras was created in Python and is built upon TensorFlow. It makes quick experiments possible. It operates on both CPUs and GPUs and covers both CNNs and RNNs.

3.6.3 PYTORCH:

PyTorch is a tool that may be used to build deep neural networks and run tensor calculations. A Python-based software called PyTorch offers Tensor calculations. A framework for building computational graphs is provided by PyTorch..

3.6.4 CAFFE:

Caffe was created by Yangquing Jia and is also free source. Caffe differs from various other frameworks in terms of rapid processing and ability to learn on images. We can easily address a variety of problems thanks to the pre-trained models we may access using the Caffe Model Zoo framework..

3.6.5 DEEPLEARNING4j:

Because Deeplearnig4j is programmed in the programming language Java, it is more effective than Python. The Deeplearn-ing4j ND4J tensor library offers the ability to interact with arrays of dimensions or tensors. CPUs and GPUs are supported by this framework. Deeplearning4j supports plain text, csv, and pictures.

Name	Platform	Written In	Cuda	Parallel Execution	Trained Model	RNN	CNN
Tensorflow	Linux, Window,MacOs, Rasbian,Mobile, Webapp	Python, C++, Cuda	Yes	Yes	Yes	Yes	Yes
Pytorch	Linux, Window, MacOs	Python, C++, Cuda	Yes	Yes	Yes	Yes	Yes
Keras	Linux, MacOs, window	Python	Yes	Yes	Yes	Yes	Yes
Mxnet	Linux, Window, Mac,Mobile, Webapp	C++, Python, R, Julia, Scala, Go, Perl	Yes	Yes	Yes	Yes	Yes
Deeplearning4j	Window, Linux,Mac, Mobile	Java, Scala, Cuda, C++, Perl, Python, Closure	Yes	Yes	Yes	Yes	Yes
Microsoft CNTK	Window, Linux	C++	Yes	Yes	Yes	Yes	Yes

Table 3.2 Comparison of Deep Learning Frameworks

3.7 APPLICATIONS OF DEEP LEARNING

Deep learning is used in a variety of applications, such as self-driving cars, the processing of natural language, Google's Artificial Intelligence Virtual Assistant, Visually Recognition, Illegal activity Detection, Health Care, Adding Sound to Silence Movies, recognizing Developing Delay in Children, Automatically Machine Translation, which was published Text to Picture Translation, which was published Illustration to Picture Synthesis, Straightforward Image Awareness, Image designation Earthquake categorization Market-Rate Prediction, News Aggregation, and more.

3.8 CONCLUSION

Although deep learning is constantly evolving, there are still many problems that need to be solved and can be done so by using deep learning. We can utilise deep learning to make computers smart—sometimes more intelligent than humans despite the fact that the precise process underlying it is still a mystery. Right now, the objective is to develop neural network smartphone models that will improve the applications' intelligence and cunning. Make the field of deep learning more devoted to developing mankind and improving the quality of life in the global community.

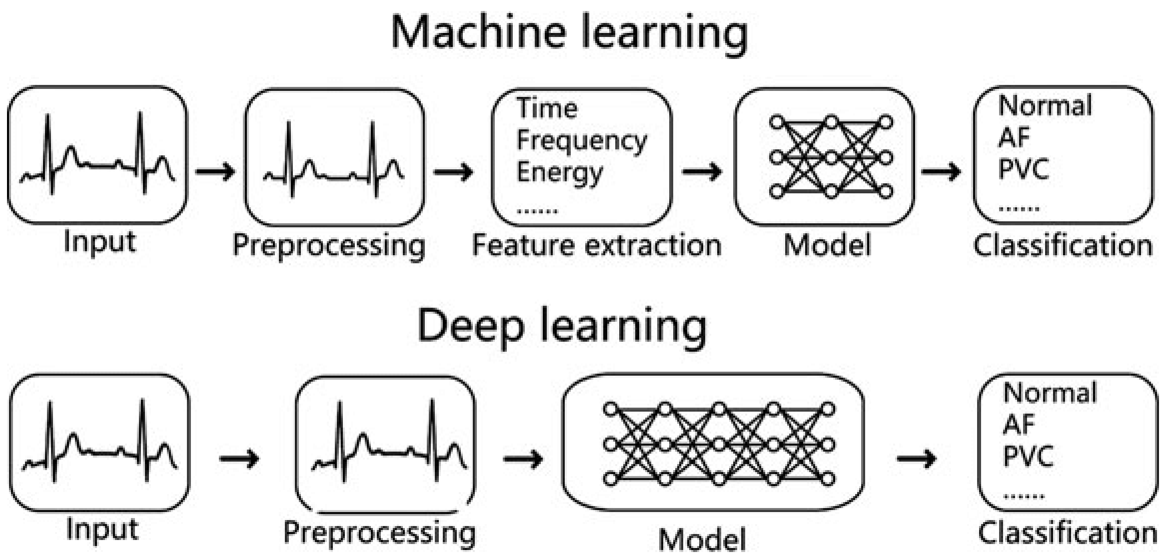


Fig 3.3 Comparison of Machine learning and deep learning

Deep learning has numerous applications in machine vision, audio recognition, and processing natural language, among others. Deep learning have many benefits, one of which is that it can automatically learn features from the data, negating the need for hand-engineered characteristics. This is especially helpful for tasks like picture recognition when the features are hard to describe.

Deep learning, a branch of machine learning, uses neural networks with artificial intelligence (ANNs) to model and solve complex problems. The idea behind it is to build deep neural networks, which are synthetic neural networks with many layers and the capacity to learn a hierarchical structure of the input.

CHAPTER 4

CONVOLUTION NEURAL NETWORK

4.1 CNN ARCHITECTURE

In essence, CNN's architecture is a list of layers that convert a 3-dimensional picture volume—that is, its width, height, and depth—into a 3-D output volume. A N*N filter is applied to the image being used by connecting each neuron in the subsequent layer to a little portion of the resultant image from the layer before. This is an important fact to remember.

It makes use of M filtration systems, which are essentially feature extraction tools that pull out features like corners, edges, and so on.

The usual architecture of CNN is depicted in the illustration below.

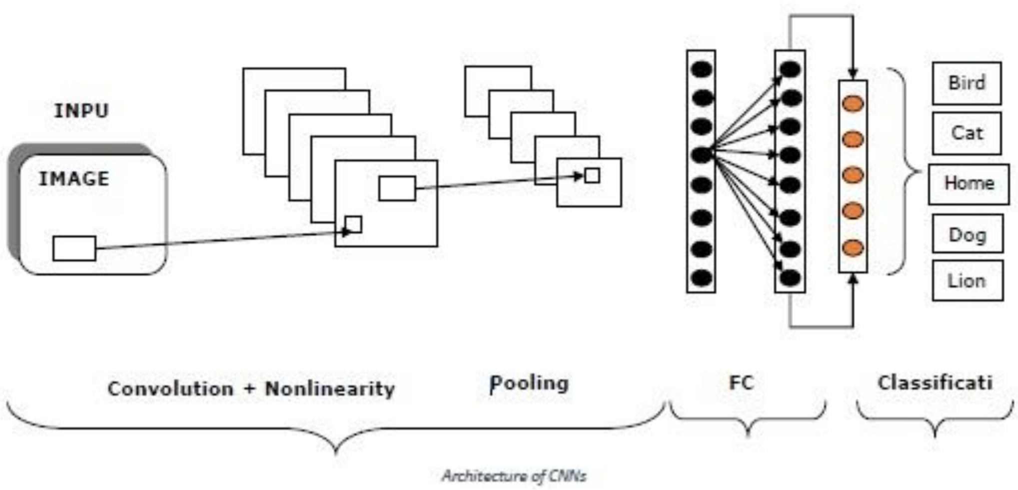


Fig 4.1 Typical Architecture of CNN

The deep learning network architecture that directly learning from data is called a convolutional neural network (CNN). Finding patterns in photos to identify items using CNNs is extremely useful. For classifying non-image data, such as time series, sound, and signal data, they can be quite helpful.

4.2 CNN LAYERS

4.2.1 CONVOLUTIONAL LAYERCONV)

They are in charge of performing convolution operations and act as CNN's foundation. The Kernel/Filter (matrix) in this layer performs the convolution process. Until the complete image is scanned, the kernel produces horizontal and vertical modifications dependent on the stride rate. The kernel is deeper even though it is tiny than a picture. If the picture has 3 (RGB) channels, the kernel's width and height will be small in size, yet the depth of the image will cover all three.

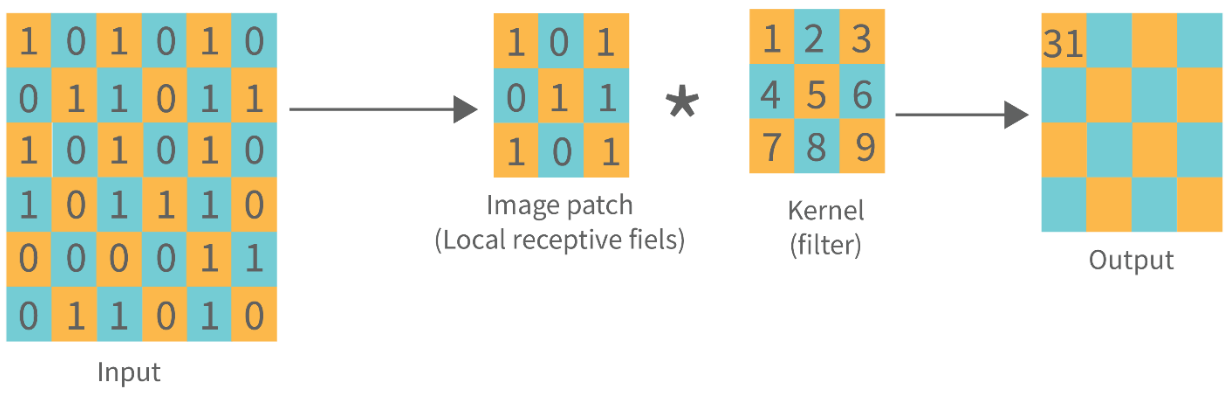


Fig 4.2 Convolutional Layer

In addition to convolution, convolutional layers also include the Non-linear activation function, which is a crucial element. The results of linear procedures like convolution are subjected to a non-linear activation function. Smooth nonlinear functions like the sigmoid or the hyperbolic tangent (tanh) function were frequently used in the past, despite the fact that they are mathematical representations of real neuron activity. The rectified linear unit (ReLU) is now the most well-liked non-linear activation function. $f(x) = \max(0, x)$.

4.2.2 POOLING

The features identified by the convolutional layer map of features are combined by CNN using pooling layers, as the name suggests. It essentially helps to minimise overfitting throughout the training of the model by compressing or applying the characteristics in the feature map. Pooling layers are extremely simple because they often use the highest or median values of the input to reduce the data.

Pooling layers, as we've seen, reduce the dimension of feature maps. As a result, if the framework or dimension of any information are high, we can use pooling layers with the convolutional layer to convert the multidimensional map of features produced by the convolutional layer to a low-dimensional one, requiring less computational effort overall. By pooling layers, the feature map is summarized, negating the need for the algorithm to be trained on exactly placed features. As a result, a model gets more reliable and sturdy.

Types of pooling layers

Roughly we can divide pooling layers into three categories.

- **Max pooling layer**
- **Min pooling layer**
- **Average pooling layer**
- **Global pooling layer**

4.2.2.1 MAX POOLING:

The layer in max-pooling uses the prominent feature of the convolutional layer's map of features. In a nutshell, it selects the element from the area that a filter in any feature map has gathered that has the highest value. The diagram below illustrates how the max poling layer works using a two-dimensional feature map.

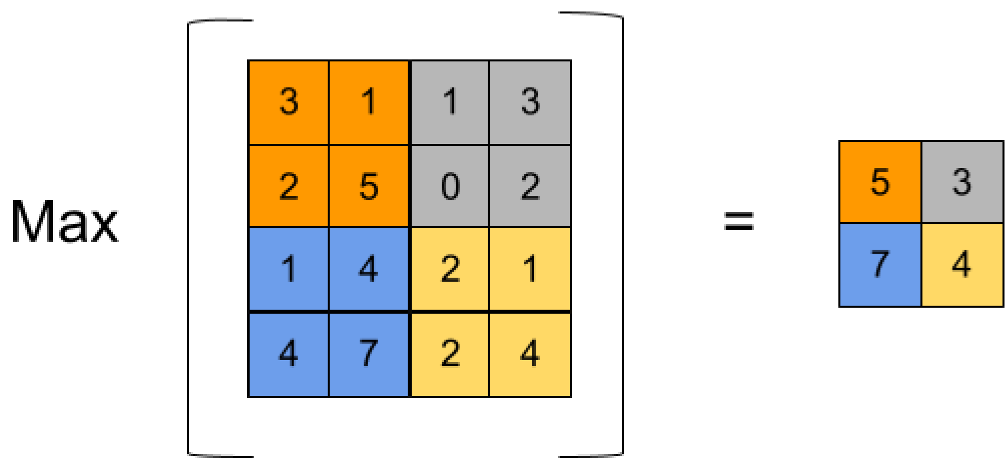


Fig 4.3 Max Pooling layer

The clearest features are the most effective lower- depictions of the image when applied to image processing, and the most pronounced features are extracted from the image via max-pooling. Edges, points, and other low-level features can be extracted from the data with the help of max polling.

4.2.2.2 MIN POOLING:

When using min pooling, the convolutional layer's feature map's least prominent feature is used by the layer to operate. More specifically, we can state that it chooses the element with the lowest value from the region that the filtering algorithm in any feature map has collected..
The 2-dimensional feature map in the figure below illustrates how the min pooling layer functions.

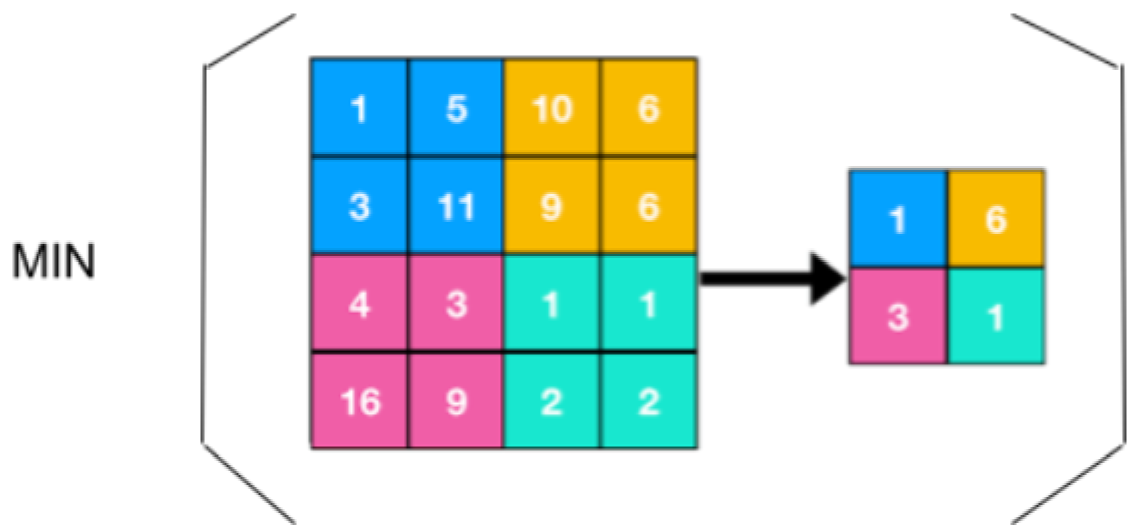


Fig 4.4 Min pooling layer

We utilise the min pooling approach, as shown in the illustration above, to identify the features from the information that are essentially insignificant, or, if we are speaking about image data, the aspects that have lower sharpness values or the categorisation features from the image..

4.2.2.3 AVERAGE POOLING:

The layer selects an average values of the components contained in a feature map patch when utilising average pooling. The whole feature map is essentially down sampled to the mean value collected by the particular feature map area. Max pooling gives the most obvious characteristic of any patch, as opposed to average pooling, which provides the median of the area that is covered. The image below shows an example of a normal pooling of a 2*2 feature map from the pooling layer and a 4*4 image.

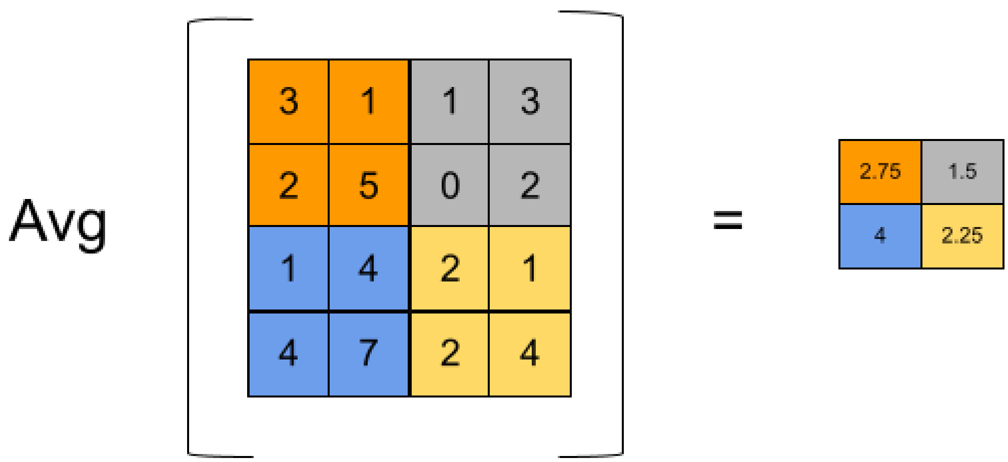


Fig 4.5 Average pooling

Through pooling, we achieve a few translations invariance. Convolutions also require more time to compute than pooling. When we use average pooling, it is simpler to extract the smooth features. When the average pooling layers are applied to the image data, all of the colours visible in the feature map's coverage region will be combined. Therefore, we can use average pooling to obtain accurate answers if the average number of data points within the image's information and colour is even, or to put it another way, if the dispersion is correct.

4.2.2.4 GLOBAL POOLING:

Because the global pooling layer passes the resulting vector into the softmax layer straight after calculating the mean or highest of the feature map, which lessens the chance of overfitting, we can basically divide it into two types.

- Global average pooling.
- Global max pooling

4.2.2.4.1 GLOBAL AVERAGE POOLING:

The global average pooling layer averages each feature map, and the activation layer receives the mean value from it.

4.2.2.4.2 GLOBAL MAX POOLING:

The global max-pooling layer passes the largest value from every feature map to the activation layer in a completely linked layer.

The global average pooling layer's operation can be seen here.

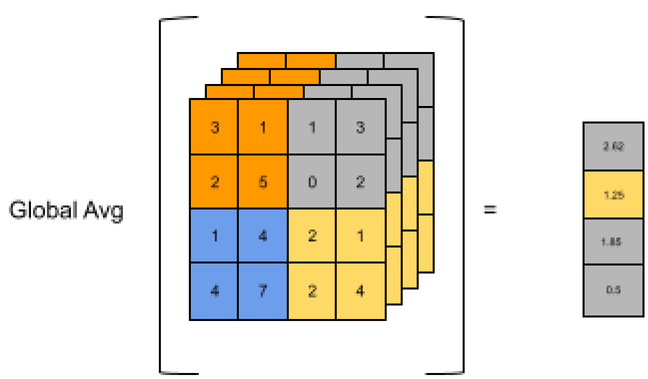


Fig 4.6 Global Max Pooling:

4.2.3 RELU

The Rectified Linear Unit, or ReLU, is not given its own phase in the convolutional neural network process. The process of convolution that we talked about in the last session is supplemented by this procedure. Despite the fact that some educators and authors discuss the two processes separately, we will consider them both to be a part of the first stage in our methodology. Using the rectification function will increase the nonlinearity of our images. Given that photographs are intrinsically non-linear, we wish to achieve that. Any image you examine will demonstrate that it contains numerous non-linear components.

The rectifier functions to further split up the uniformity in order to make up for any linearity we could impose on a picture when we put it via the convolution process. To further understand how that truly functions, we may examine the subsequent image and see the changes that occur during the convolution and rectification processes.

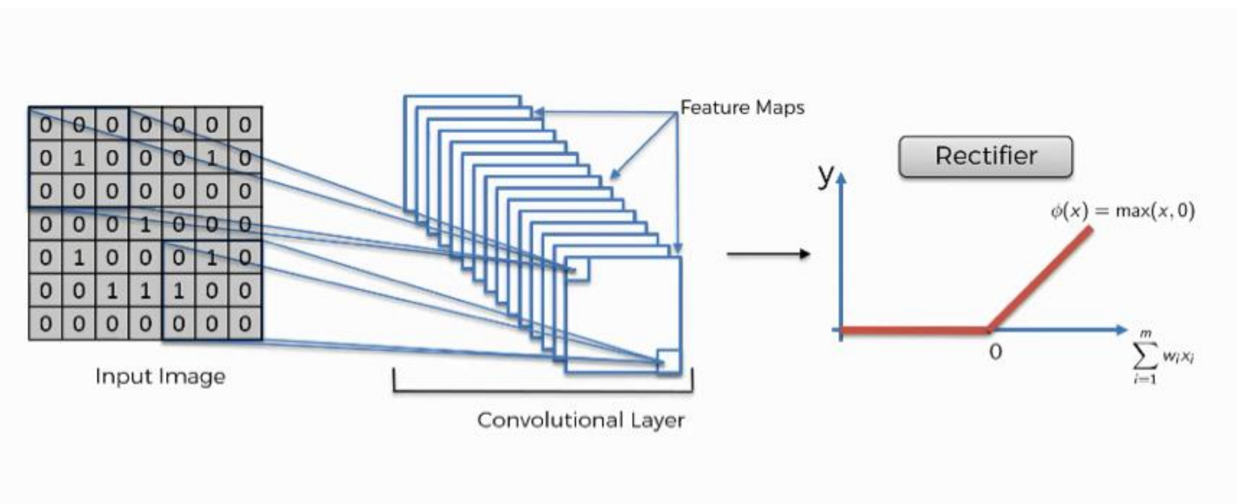


Fig 4.7 ReLu Layer

4.2.4 FULLY CONNECTED LAYER (FC):

Each input is coupled to a specific neuron according to the fully connected layer's (FC) flattened input method. The standard arithmetic functional operations are then performed on the flattened vector via a few more FC levels. The classifying process officially starts at this point. In CNN architectures, FC layers are frequently found near the very end.

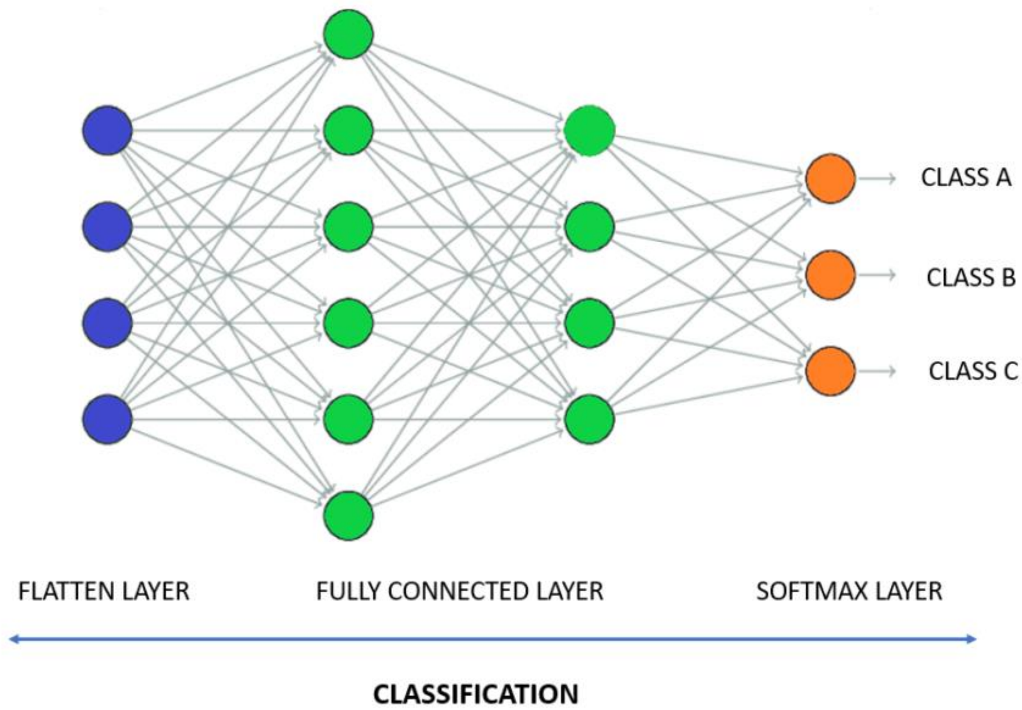
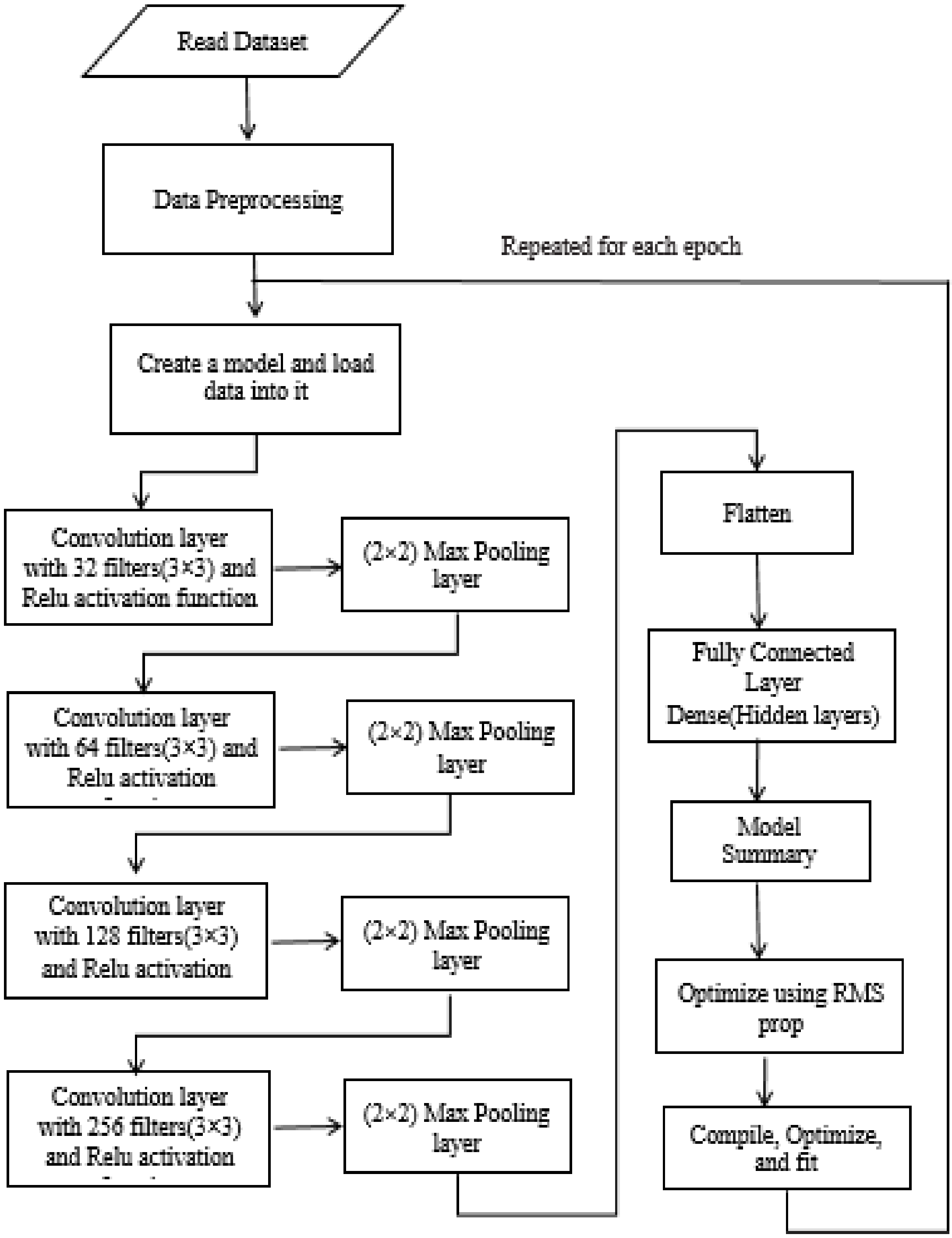


Fig 4.8 Fully connected layer

The Deep Neural Network's Classification portion includes the Flatten Layer, Fully Connected Layer, and Softmax Layer combination.

CHAPTER 5

WHITE BLOOD CELL SUBTYPES



5.1 DATASET

The dataset consists of 12,444 images of both training and testing. 9,957 of the 12,444 photos were used to train the model, while 2,487 were used to test the model.

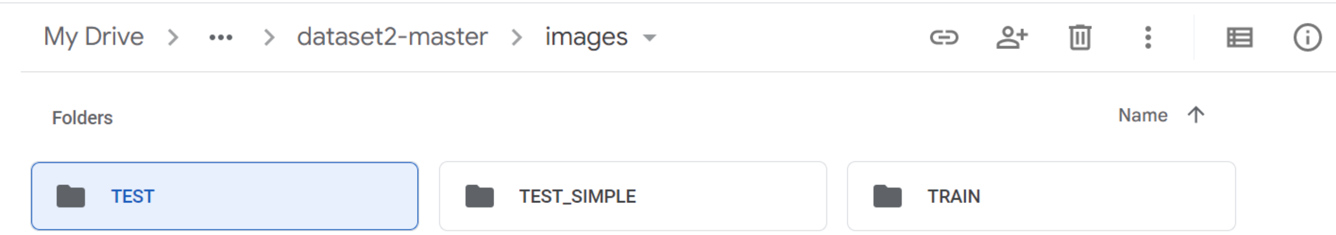


Fig 5.1 Testing dataset

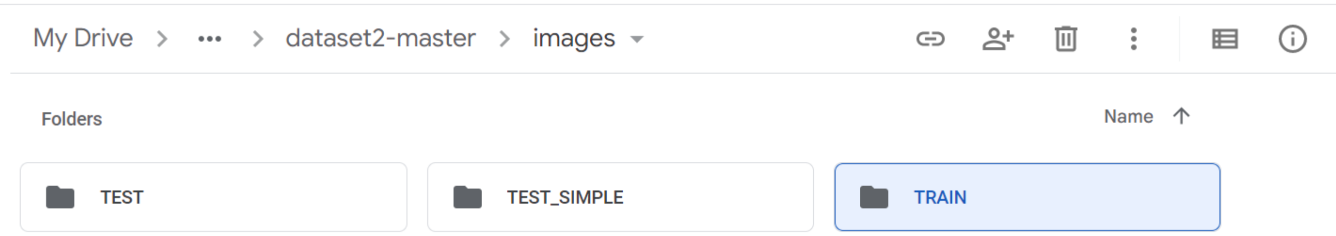


Fig 5.2 Training dataset

Those 9,957 images of training data were subdivided into 4 types of white blood cells:

EOSINOPHIL - 2,483

LYMPHOCYTE - 2,497

MONOCYTE - 2,499

NEUTROPHIL - 2,478

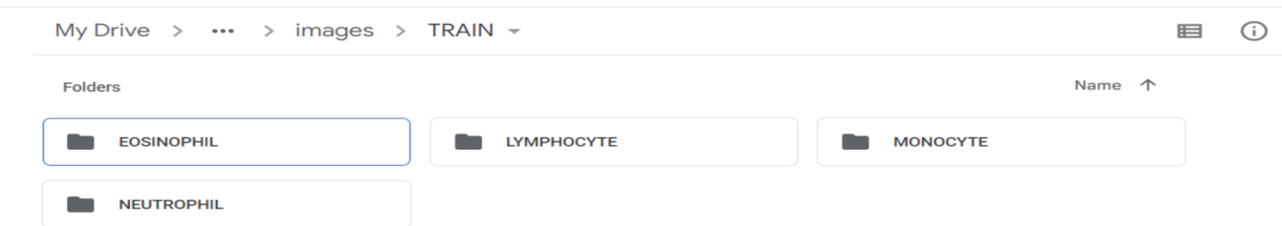


Fig 5.3 WBCs trained dataset subtypes

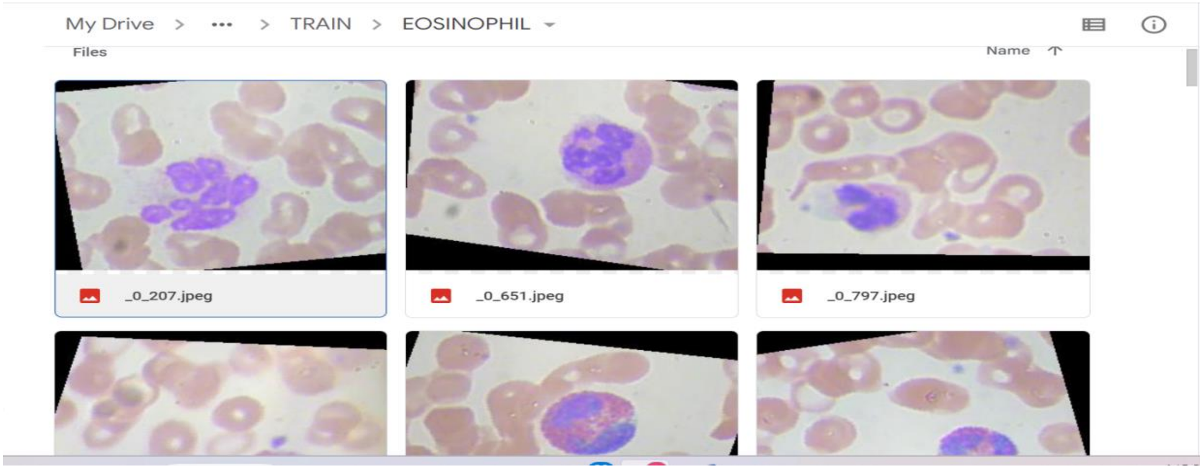


Fig 5.4 Trained Images

Those 2,487 images of testing data were subdivided into 4 types of white blood cells:

EOSINOPHIL - 624

LYMPHOCYTE - 620

MONOCYTE - 623

NEUTROPHIL - 620

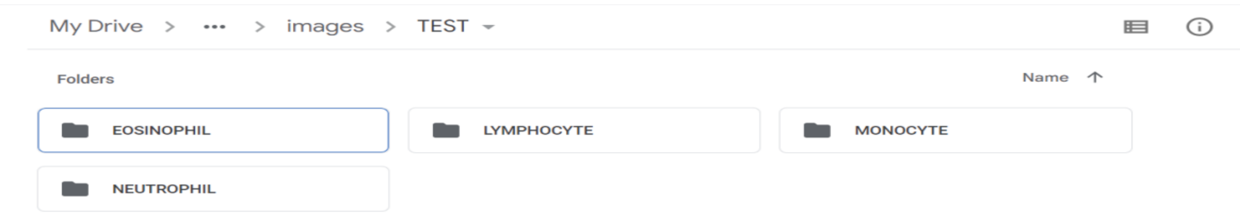


Fig 5.5 WBCs testing dataset subtypes

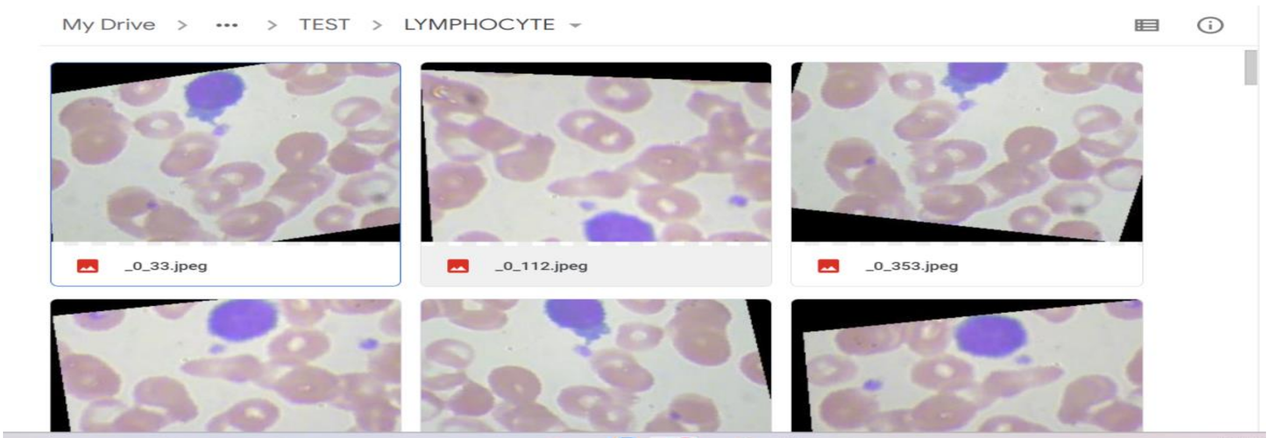


Fig 5.6 Testing Images

5.2 DATA PREPROCESSING

The images of training data and testing data are of different sizes, so in data preprocessing all the images resize to a certain size (120,120,3) .

The four white blood cells are labeled with different labels:

Binary(label 0, label 1)

Multi(label 0, label 1, label 2, label3)

After labeling the white blood cells, every image changes to array datatype to process through the CNN algorithm.

Then the array values were appended into x_train_multi & y_train_multi and x_test_multi & y_test_multi.

Using One Hot Encoding, the labels were assigned to the classes as it is multi classification the classes were divided into 4 classification.

y_train_multi to y_trainHot_multi and y_test_multi to y_testHot_multi.

```
100%|██████████| 2483/2483 [00:35<00:00, 70.21it/s]
100%|██████████| 2497/2497 [00:32<00:00, 76.37it/s]
100%|██████████| 2499/2499 [00:31<00:00, 80.24it/s]
100%|██████████| 2478/2478 [00:32<00:00, 75.55it/s]
100%|██████████| 620/620 [00:08<00:00, 69.74it/s]
100%|██████████| 624/624 [00:15<00:00, 40.15it/s]
100%|██████████| 620/620 [00:12<00:00, 48.43it/s]
100%|██████████| 623/623 [00:11<00:00, 54.74it/s]
```

Using TQDM module the progress bar appears at the output console which acknowledge the images loaded from train and test to the x_train_multi and x_test_multi.

5.3 CONVOLUTION NERUAL NETWORK

Convolutional neural networks are one of the primary forms of neural networks utilized to recognise and categorise images. Face recognition, object identification, and other tasks are commonly performed with CNNs. Convolution neural networks constitute a subset of neural networks in which generic matrix multiplication is replaced by convolution in at least one layer rather than multiplication. Convolution is used as the first layer to extract features from the image being input. Convolution keeps the connection between pixels by inferring visual characteristics from tiny squares of input data. It is an algebraic procedure with two inputs, like a kernel or filter and an image matrix.

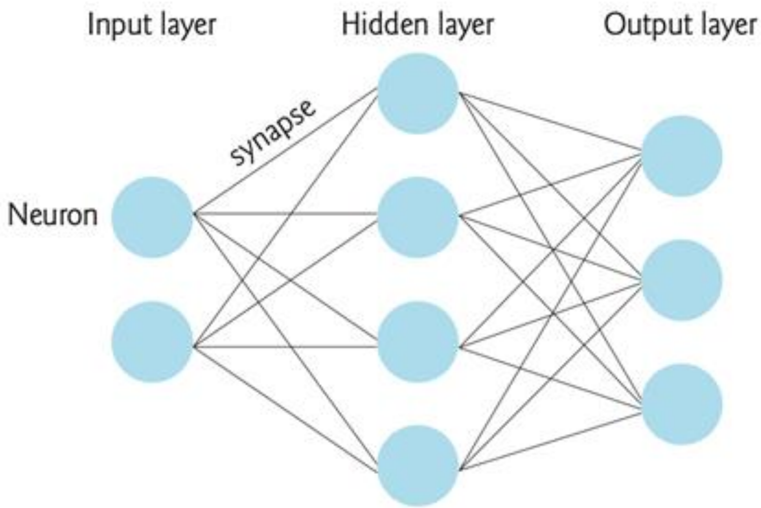


Fig 5.7 Convolution neural network

Convolutional neural networks can be implemented using the following four layered concepts:

- **Convolution**
- **ReLu**
- **Pooling**
- **Fully Connected Layer**

Images are processed and then categorised by CNN according to predetermined categories before being used as input. Machines perceive image input as an array of pixels, according to the image resolution. H1 x w1 x d1, where h1 stands for height, w1 for width, and d1 for dimensions, will appear depending on the image resolution. Think of the RGB matrix picture with the dimensions 6 x 6 x 3 and the image with the dimensions 4 x 4 x 1 as examples. Technically, each input image for CNN's in-depth learning models for training and testing will travel via number of convolution layer with the filters (Kernels), Pooling, fully integrated layers , and use Soft-max function to identify an item with a value that may be between 0 and 1.

5.3.1 CONVOLUTION

Convolution is the first layer of the CNN technique used to extract features from an image that is input. Convolution mathematically maintains the connection between pixels by learning visual properties from tiny input data squares. A filter and an image matrix are its two inputs.

- An image matrix dimensions = (h1 * w1 * d1)
- A filter = (f_h1* f_w 1*d2)

- Output = (h1 - f_h 1+ 1) *(w1 – f_w 1+ 1) * 1

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau \qquad \text{Eq 5.1}$$

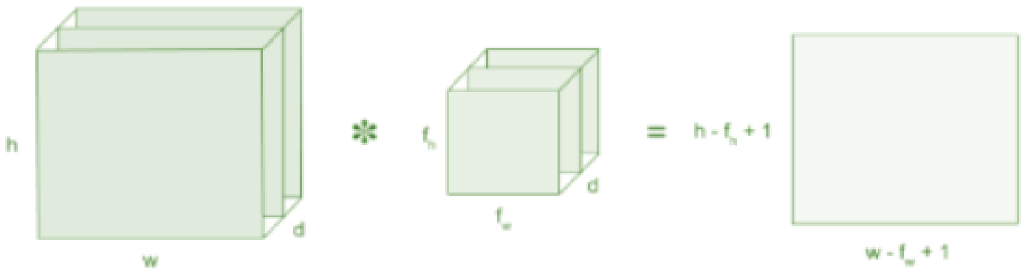


Fig 5.8 Convolution layer

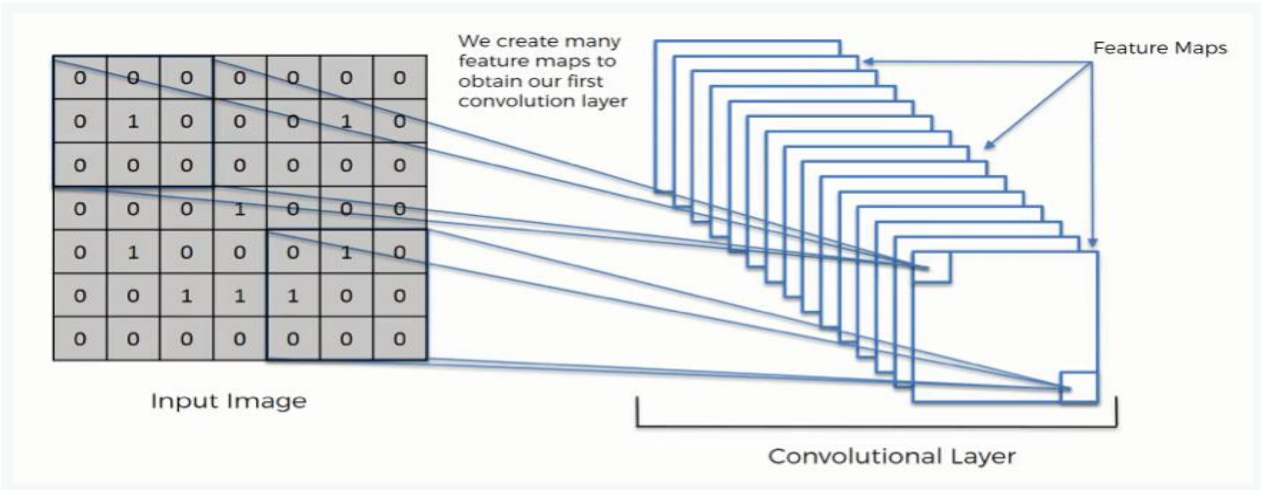
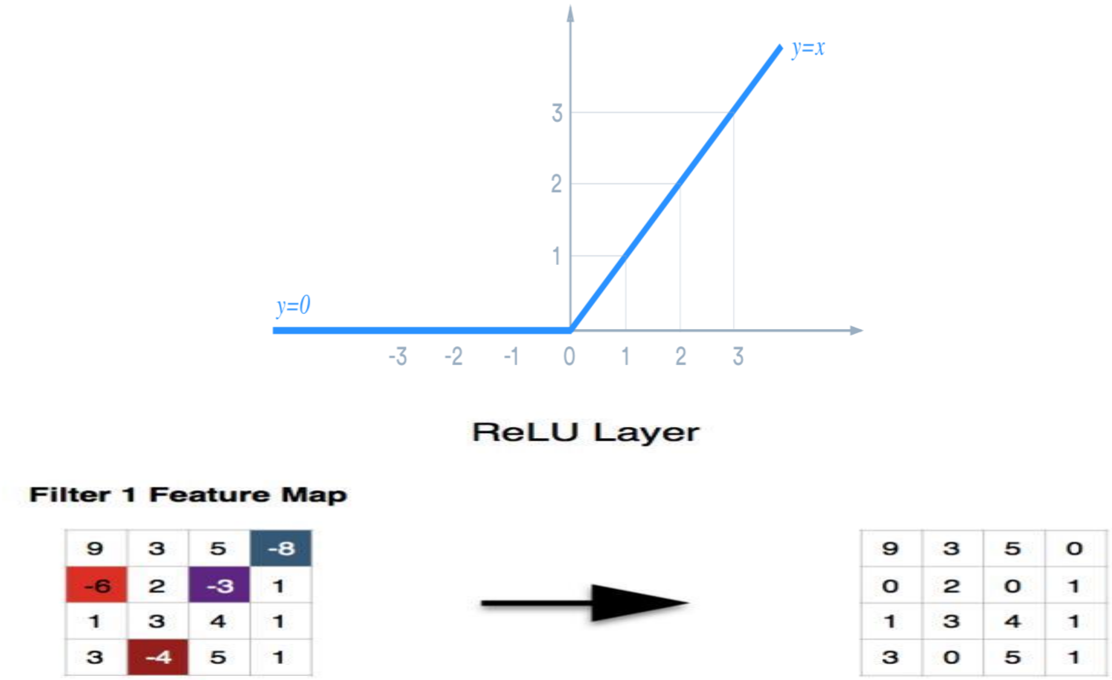


Fig 5.9 Feature Maps

The fundamental benefit of convolving a picture is that it offers a variety of operations, including edge detection, blur, and sharpen, that may be done when convolving with various filters.

5.3.2 ReLU

The term "non-linear operation" is "rectified linear unit," or "ReLU". ReLU, as it is commonly referred as, is a linear function with a piecewise structure that, when the input value is positive, produces the input directly; when it is negative, it generates zero. It is now the standard activation function for an extensive variety of neural network types, including CNN.



ReLu = max(0,x)

Fig 5.10 ReLu Layer

5.3.3 POOLING

When the photos are too big, the pooling layer is employed to cut down on the amount of parameters. We reduce the size of the picture array in this layer. The pooling layers go through four stages.

- Select the window size.
- Select a stride (usually 2)
- Glance at your filtered photographs through your window.
- Select the highest value from each panel.

The pointer denotes that the largest element from the revised feature map is chosen via Max pooling. Instead of only using the biggest component, one may use the average pooling. Sum pooling is the process of adding up all the feature map components.

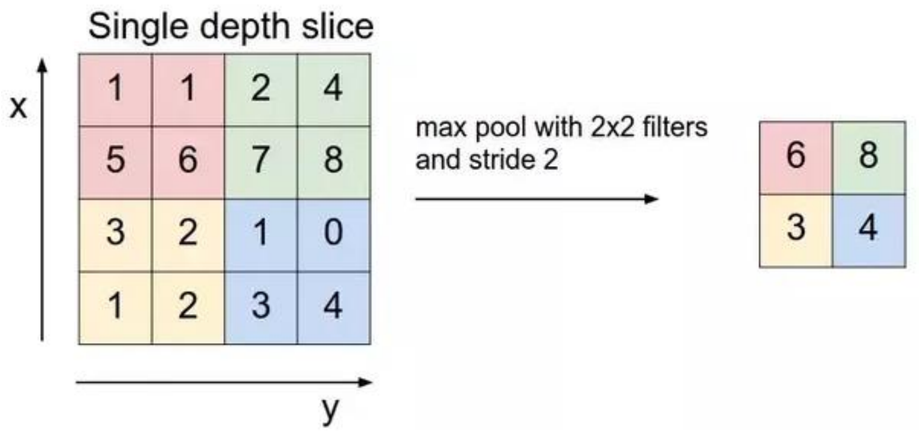


Fig 5.11 Pooling layer

5.3.4 FLATTEN LAYER

The combined feature map flattens into a column at this point. Because we must eventually enter the information into an artificial neural network, we take this action.

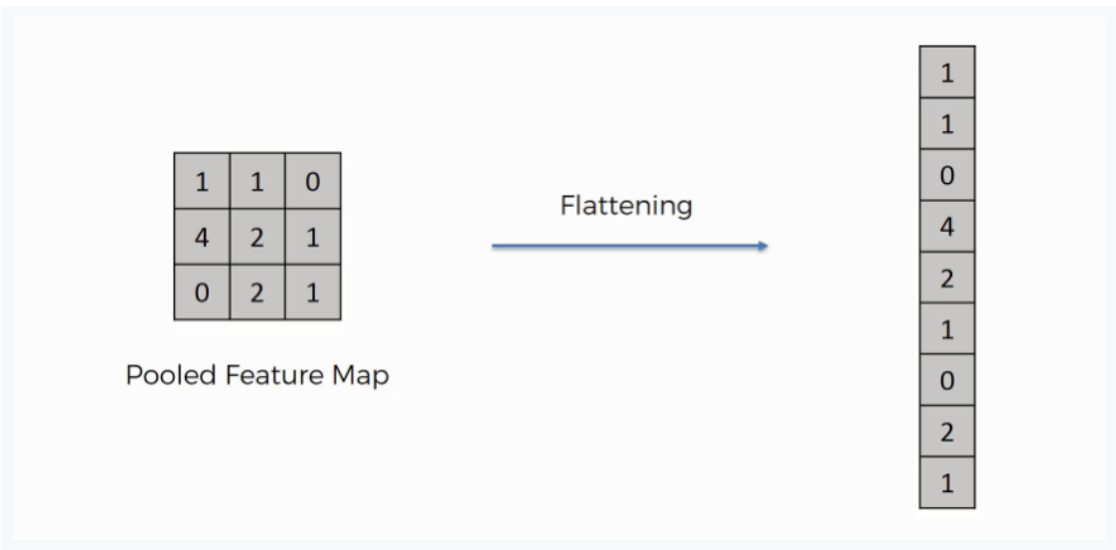


Fig 5.12 Flatten layer

After the flattening stage, you are left with a large vector of input data, which you send into the artificial neural network for further analysis.

Fig 5.13 Flattening after pooling layer

5.3.5 FULLY CONNECTED LAYER

Our matrix was transformed into a vector then entered into CNN's fully connected layer, an upper layer resembling a neural network. In the diagram below, the feature map matrix is going to be changed into a series of vectors (x1, x2,..., Xm). By combining these attributes, a model was created utilising the completely linked layers.

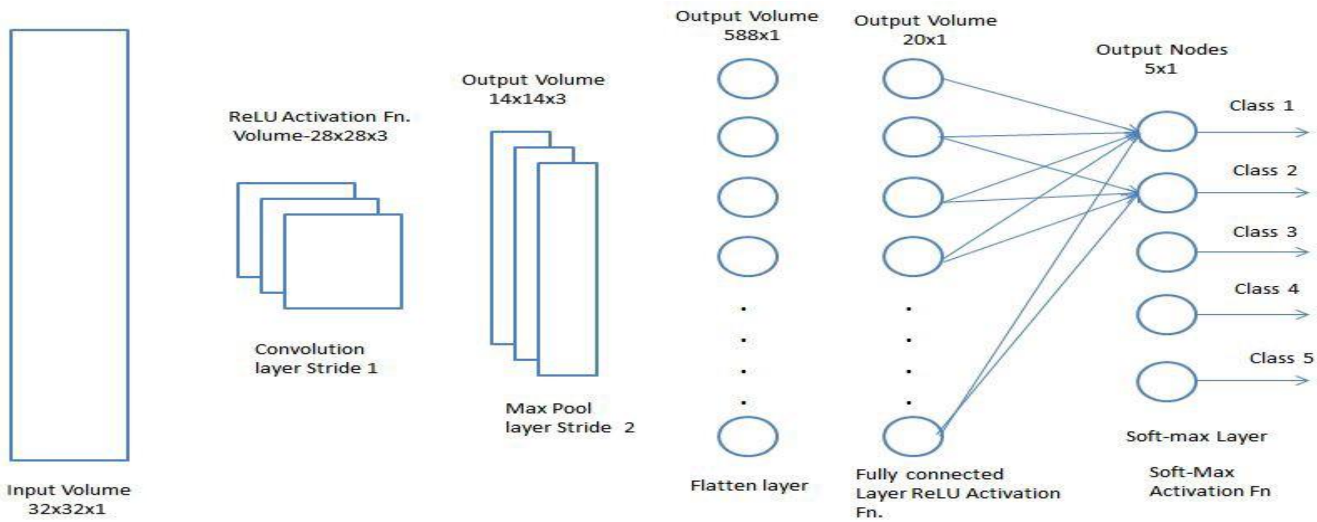


Fig 5.14 Fully Connected Layer

The practical operation of this whole connection is as follows:

- A specific feature is detected by a neuron in the fully linked layer.
- It keeps its worth.

- It conveys this significance to both the “class1”, “class2”, “class3” and “class4” classes.
- All these classes examine the feature of images and determine its applicability to them.

The fully connected layer using SOFT-MAX(multi/binary) and SIGMOID(binary) function the classification takes place.

RESULTS

All of the outcomes from the suggested model are included in this section. On Google Colab, the proposed model is simulated. Different performance criteria, including precision, sensitivity, F1 score, and accuracy are taken into consideration for the examination of the suggested model.

6.1 TRAINING PERFORMANCE ANALYSIS

Table 1.1 lists the training parameters for 32 batch sizes, including train loss, valid loss, error rate, and valid accuracy. Ten epochs of the simulation are run, and the results are examined on the 20th epoch.

Epoch	Train Loss	Train Accuracy	Val Loss	Val Accuracy
1	1.4072	0.2473	1.3898	0.2492
2	1.3898	0.2545	1.3916	0.2492
3	1.3796	0.2630	1.3427	0.3087
4	1.2629	0.3734	1.1686	0.4244
	….	…..	….	….
9	0.3781	0.8433	0.3026	0.8762
10	0.3068	0.8761	0.4321	0.8284
11	0.2495	0.9066	0.2436	0.9144
12	0.1846	0.9299	0.4016	0.8549
	….	….	….	….

17	0.0907	0.9748	0.2459	0.9526
18	0.0932	0.9747	0.2574	0.9421
19	0.0761	0.9776	0.2786	0.9469
20	0.1231	0.9806	0.3595	0.9534

Table 6.1: Training Performance of Batch Size 32

6.2 PERFOMANCE METRICS:

The performance measurements (FN) are produced using a variety of confusion matrix characteristics, including True Positive (TP), False Positive (FP), True Negative (TN), and False Negative. The confusion matrix's parameters are as follows.

(a) **Accuracy**: It is described that the proportion of all accurate predictions to all noticed predictions.

(b) **Precision (P):** By dividing the total number of precise positive predictions by the total number of positive predictions, it is calculated.

(c) **Specificity (Sp):**It is calculated by dividing the total number of negatives by the proportion of correctly predicted negative outcomes.

(d) **Sensitivity (Se):** By dividing the total positives by the percentage of accurate positive forecasts, it is calculated.

6.3 CONFUSION MATRIX:

The efficiency of a classification model is evaluated using a N x N matrix termed a confusion matrix, where N is the overall amount of target classes. The machine learning model's predicted goal values are compared to the actual goal values in the matrix. A confusion matrix is a graph that shows how many correct and incorrect classifications a classifier made. It is used to assess the performance of a classification model. It is possible to use it to determine performance metrics like accuracy, precision, recall, and F1-score in order to evaluate a classification model's efficacy.

In the field of machine learning, and more specifically the problem of stastical classification, an error matrix is a particular table layout that enables visualising the performance of an algorithm, usually a supervised learning one (in unsupervised learning, it is usually referred to as a matching matrix). The literature describes both iterations of the matrix, where every row provides instances in a real class and every column provides cases in a predicted class. The name was selected since it is easy to tell if the system is fusing two classes together (i.e. frequently mislabeling one as another).

CLASSES	CLASS 0	CLASS 1	CLASS 2	CLASS 3
CLASS 0	602	20	2	0
CLASS 1	59	561	0	4
CLASS 2	30	0	590	0
CLASS 3	1	0	0	619

Table 6.2: Confusion matrix of CNN model of entire dataset

The confusion matrices for the entire dataset for the CNN model are shown in table 1.2. These matrices demonstrate the accuracy of several forecasts. The diagonal values generate a precise number of images that may be categorised using the given model, and each column is tagged with the appropriate class name.

Plots of Train and Validation accuracy Vs No.of epochs:

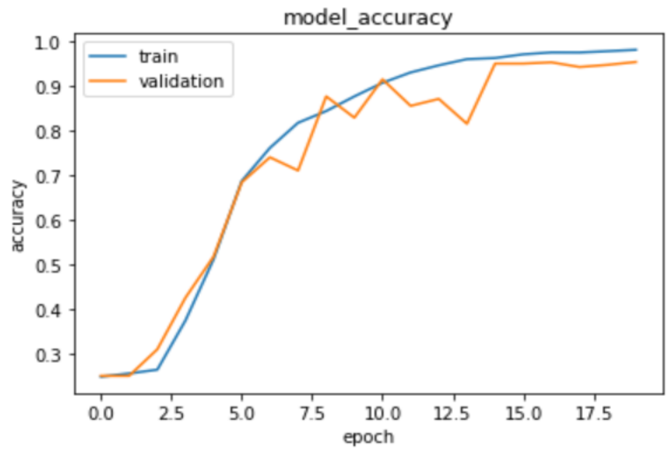


Fig 6.1 : Model_acuuracy

Plots of Train and Validation loss Vs No.of epochs:

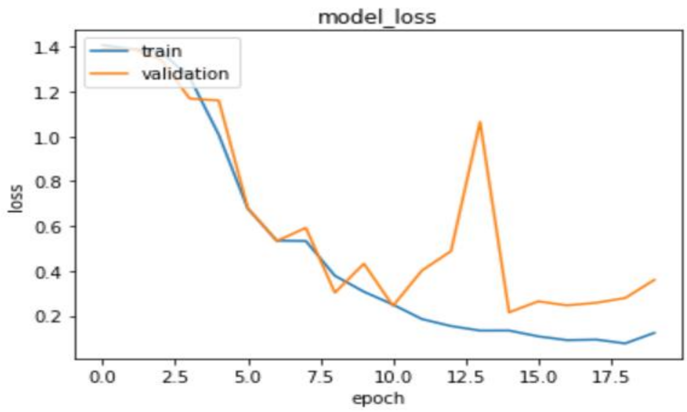


Fig 6.2: Model_loss

6.4 CLASSIFICATION REPORT:

The visualisation of the classification report shows the model's precision, recall, F1, and support scores.

❖ The classification report visualizer displays the model's precision, recall, F1 and support scores.

- ❖ Recall is the capacity of a system of classification to locate all occurrences that are favourable.
- ❖ The F1 score, with 1.0 denoting the best outcome and 0.0 the worst, is a balanced harmonic average of recall and precision.
- ❖ Support is the proportion of actual occurrences of the class in the dataset.

CLASSES	PRECISION	RECALL	F1-SCORE	SUPPORT
0	0.87	0.96	0.91	624
1	0.97	0.90	0.93	624
2	1.00	0.95	0.97	620
3	0.99	1.00	1.00	620

Table 6.3: Classification Report

6.5 CLASSIFICATIUON MEASURE

It is essentially a longer version of the confusion matrix. There are other metrics besides the confusion matrix that may be used for analysing and evaluating the performance of our model.

a. Accuracy

b. Precision

c. Recall (TPR, Sensitivity)

d. F1-Score

6.5.1 ACCURACY

Simply put, accuracy indicates how often the classifier makes accurate predictions. It is the ratio of correctly predicted events to all predicted events. The accuracy metric does not work well for imbalanced courses. Accuracy has its own downsides. When the model forecasts that each point corresponds to the majority of class label with data that is imbalanced, the accuracy will be high. The model is unreliable, though.

It serves as a gauge of the degree of real-world forecast accuracy reached. It explains the ratio of accurate positive forecasts to all favourable projections in plain English.

Accuracy is a valid choice of evaluation for classification issues that are appropriately balanced, not distorted, or where there is a no class imbalance.

accuracy			0.95	2488
macro avg	0.96	0.95	0.95	2488
weighted avg	0.96	0.95	0.95	2488

Fig 6.3: Accuracy

The evaluation's findings showed that our technique is very accurate, real-time, and capable of classifying a variety of categories. Since the model's overall accuracy is 95%, the trained models have performed admirably.

6.5.2 PRECISION

It is an indicator of the level of accuracy attained in real prediction. Simply said, it informs us of the proportion of favourable predictions that actually come to pass.

Precision is defined as the proportion of the total number of positively categorised positive classes to the entire number of positively predicted positive classes. Alternatively, the proportion of correctly predicted events among all the predictively positive classes. High accuracy is necessary (preferably 1).

When False Positives are more problematic than False Negatives, precision is a valuable indicator.

6.5.3 RECALL

It counts the number of observations in the positive class that are actually expected to be favourable, or the number of actual observations that are correctly predicted. Sensitivity is another word for it. Recall is a fantastic alternative for an evaluation statistic when our goal is to find as many positive as feasible.

The percentage of correctly categorised positive classes to all favourable classes is known as recall. On the other hand, the amount of all the beneficial categories we correctly predicted. Recall should be significant (preferably 1).

"The percentage of correctly categorised positive classes to all favourable classes is known as recall."

6.5.4 F1 score

The F1 score, which ranges from 0 to 1, represents the harmonic mean of recall and precision. We opt for the harmonic mean since it is less prone to extremely high values than simple averages.

The F1 score essentially maintains the equilibrium between your classifier's precision and recall. If your recall is weak, your precision will also be weak, which will lower your F1 score.

There will be situations where it is difficult to determine whether Precision or Recall is more crucial. We mix the two!

In truth, the recall drops when we try to improve our model more accurate and vice versa. The Both trends are represented by a single number in F1-score.

6.6 CONCLUSION

This paper employs the convolution neural network technique to assist hematologists in classifying white blood cells into their subgroups. This classification aids in identifying the subtype and determining the illness that a patient is dealing with. Accuracy refers to how closely the measured number matches the current value. As we mentioned, when an unlabeled picture is put through the deep learning process, convolution neural methodology is used instead to take advantage of the hidden data and classify the images according to their subtype. In this study, the classification of each subtype is completed more quickly and with a 95% success rate.

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