Analysis on Covid-19 Detection System Using Machine Learning & Deep Learning Models

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APPROVAL

The thesis paper titled "Analysis on Covid-19 Detection System Using Machine Learning & Deep Learning Model" submitted by Nuzhat Tabassum Rithin (ID: 2018-1-50-003), Joy Das(ID: 2018-1-50-008), Bijoy Das(ID: 2018-1-50-009) to the Department of Electronics and Communications Engineering, East West University, Dhaka, Bangladesh has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Information and Communications Engineering and approved as to its style and contents.

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DECLARATION

We declare that our work has not been previously submitted and approved for the award of a degree by this or any other University. As per of my knowledge and belief, in this thesis contains no material previously published or written by another person except where due reference is made in the paper itself. We here-by, declare that the work presented in this thesis is the outcome of the investigation performed by us under the supervision of Dr. Anup Kumar Paul, Chairperson and Associate Professor, Department of Electronics & Communications Engineering, East West University, Dhaka, Bangladesh.

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DEDICATION

This paper is dedicated

To

Our beloved Parents and honorable teachers

ACKNOWLEDGEMENT

We would like to thank our supervisor, Dr. Anup Kumar Paul, for his encouraging words and advice during our research of the topic and our experiment. His commitment to contribute his time and effort is highly appreciated. In our research, he has taught us many essential lessons and strategies about Machine Learning and Deep Learning. His constant consolation gave us the assurance we needed to complete our work. Finally, we express our gratitude to the Almighty and our supervisor for their unwavering support. Without our supervisor's judicious help throughout the research process, this thesis paper would not have been achievable.

ABSTRACT

COVID-19, considered the deadliest virus of the twenty-first century, has claimed the livesof millions of people worldwide in less than two years. The respiratory disease (COVID-19) is caused by the novel coronavirus SARS-CoV-2, which originated in Wuhan, [14] Chinain late December of 2019. By October 2020, the virus already infected almost 40,000,000people dead over one million (Hopkins (2020)). This infection has rapidly expanded across China and into other nations since then, creating a global pandemic in 2020 dueto its ease of transmission from person to person via respiratory droplets. Pneumonia is another infectious condition that is frequently caused by a bacterial infection in the alveoliof the lungs. When an infected lung tissue becomes inflamed, pus forms in it. Because thevirus first affects the lungs of patients, X-ray imaging of the chest is useful for accurate diagnosis. To determine whether a patient has these conditions, experts conduct physical examinations and diagnose them with a chest X-ray, ultrasound, or a lung biopsy. In thisanalysis, we recommend using a chest X-ray to prioritize people for subsequent RT-PCRtesting. It would also aid in the identification of patients with a high chance of COVID and a false-negative RT-PCR who require additional testing. It is urgent to create auto- mated technologies that could diagnose this disease in its early stages, in a non-invasive manner, and in a shorter amount of time. However, selecting the most accurate models tocharacterize COVID-19 patients is challenging due to the inability to compare the outputsof diverse data types and gathering methods. This is the only way to remedy the issue. As a result, much research has been conducted to establish an appropriate method for diagnosing and classifying people as COVID-19-positive, healthy, or affected by other pulmonary lung illnesses. In a few earlier scholarly works, semiautomatic machine learning techniques with

limited precision were proposed.

In this study, we wanted to develop reliable deep learning approaches, which are a subsetof machine learning and AI that model the way humans acquire knowledge. Data science encompasses fields like statistics and predictive modeling, two of which benefit greatly from deep learning. One component of this is what are known as convolutional neural networks (CNN). Any automatic, reliable, and accurate screening strategy for COVID- 19 detection would be helpful for rapid diagnosis and reducing exposure to the virus for medical or healthcare personnel. The work takes advantage of a versatile and successful deep learning approach by employing the CNN model to predict and identify a patientas being unaffected or impacted by the disease using an image from a chest X-ray. In order to prove how well the CNN model was trained, the researchers employed a datasetconsisting of 10,000 images with a resolution of 224x224 and 29 batches. Convolutional neural networks (CNNs) were demonstrated to be very effective for medical picture classification. The authors of this piece propose using convolutional neural networks (CNNs)to automatically classify chest X-ray images for signs of COVID-19. Using the dataset, eleven current CNN models— max poling operation, and SoftMax activation function—that can distinguish between COVID-19 andother lung diseases—were first used to identify the symptoms of COVID-19. A stratified 5machine learning technique was utilized with a ratio of 80 percent for training and for testing (unseen folds), and 20 percent of the training data was used as a validation set to prevent overfitting problems. During the performance training, the trained model produced an accuracy rate of 98 percent. The research study can use chest X-ray pictures to identify and de-test COVID-19, normal, and pneumonia infections, according to the results of the tests.

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Problem Statement

Due to the quick increase of Covid cases, action must be taken to stop the virus's spread while also preparing for the worst-case scenario in the event that it doesn't. The proven examples are found using a variety of techniques, including deep learning, machine learning, and mathematical models, which also assist humans in comprehending and managing the problem. But because the virus is continually evolving, it is more difficult to find proven instances. Many academics are currently concentrating on innovation that is required for detecting the Covid-19 pandemic trend.

Motivation

There is evidence of a widespread epidemic known as the Spanish Flu that occurred in the 1920s. However, because the pandemic data were primarily kept on paper during that time, access to the data was limited, and it was challenging to do study on those data as well. We are currently dealing with the Covid-19 epidemic, which has been around for about 100 years. In contrast, since we live in a digital age, everything is recorded and saved in virtual storage. As a result, demand for Covid-related research has also increased dramatically [3]. Covid-19 has previously been the subject of a lot of published study. The predicting of confirmed cases is one of these issues that has been studied. Using the precise many problems can be reduced such as preparing more hospital beds if the pandemic becomes worse in the future, the severity of different measures taken by government that also impacts economy of the country can be reduced if pandemic becomes better etc. This is why we decided to choose this as a topic we should be researching upon.

Thesis Organization

There are total 5 chapters included in this research paper. This is the sequence in which the chapters are presented:

Chapter one is include with Introduction, Benefits of covid-19, AI, CNN, Purpose.

Chapter two is included with Background, Histology data in deep learning, Limitations & motivations, Image processing of Convolutional Neural Network, Literature Review.

Chapter three is included with Dataset, methodology, materials, Data pre-processing, Data processing, Classification, Proposed CNN, Convolution Layer, Max Pooling Layer, Average Pooling Layer, ReLU, Softmax Layer, CNN, Convolution, Proposed Convolution Neural Network, Fully Connected Layer, Activations Function, Dropout Layer, Backpropagation, Advantage of CNN Architecture, Applications.

Chapter Four is include with Deep Learning, How Deep Learning Works, Keras, CNN Flowchart , Methodology , Classification Report , Training & Validation Accuracy.

Chapter Five is include with conclusion and future work.

CHAPTER ONE

1. Background

1.1 Introduction

The World Health Organization named the global illness coronavirus (COVID19) a pandemic on March 11, 2020. More than 10 million instances of the Covid-19 sickness have been confirmed as of this writing, with more than 500 thousand fatalities worldwide (mortality rate: 5.3%) and more than 5 million recoveries [2]. A prompt diagnosis is essential to controlling the disease's progress and improves the efficacy of medical treatments, increasing the likelihood that the patient will survive without the need for intensive and sub-intensive care. This is important since hospitals only have a limited supply of equipment for critical care. Real-time polymerase chain reaction (RT-PCR) is the recognized gold standard diagnostic technique for viral nucleic acid detection. However, due to the disease's high contagiousness, many nations are unable to supply the necessary RT-PCR.As a result, only those with obvious symptoms are checked. Furthermore, it takes a while to provide a result. As a result, it is necessary to develop quicker and more reliable screening methods that might supplement or perhaps completely replace the PCR test.

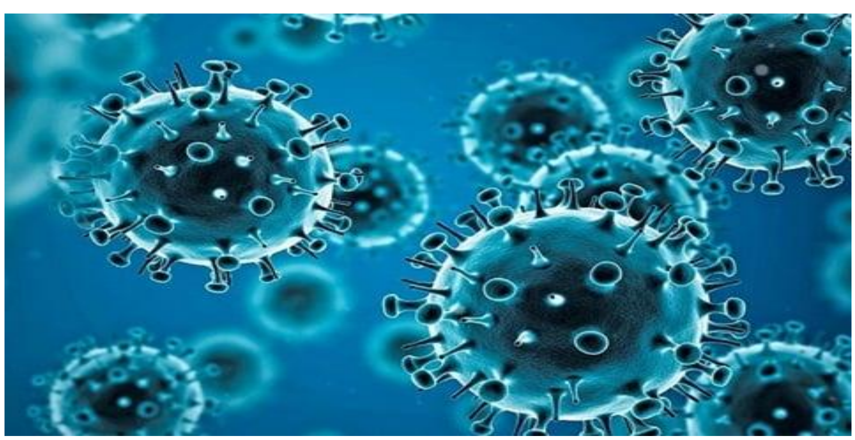

Fig 1.1: Corona Virus

Detecting COVID-19 with computer tomography (CT) imaging is a viable approach with a greater sensitivity (up to 98% com- Writing partner.Matteo.Polsinelli@graduate.univaq.it is the email address (M. Polsinelli).as comparison to 71% of RT-PCR). Given the ongoing increases in COVID-19 pneumonia patients worldwide, CT is anticipated to play a bigger role in the diagnosis and treatment of the condition. Early studies point to a pathogenic route that may be detectable with early CT, especially if the patient is examined two or more days after first exhibiting symptoms . However, the visual scanning of minute features is the greatest obstacle radiologists have while analyzing radiography pictures. Additionally, a significant quantity of CT images must be analyzed quickly, increasing the probability of misclassifications. This justifies the use of intelligent approaches that can automatically classify CT images of the chest. **[2]**

Medical imaging has made substantial use of deep learning techniques. Convolutional neural networks (CNNs) in particular have been applied for CT image classification and segmentation issues. [1] However, it is possible to mistakenly classify CT scans of the lungs that are referred to COVID-19 and not COVID-19, particularly when pneumonia-related damage from many sources is evident at the same time. In reality, pure ground glass opacities (GGO) are the most common chest CT findings although additional lesions such consolidations with or without vascular enlargement, interlobular septal thickening, and air bronchogram can also be present. Two CT images of COVID-19 and COVID-19 not are given, respectively, in Figs. 1a and b. There are now just a few COVID-19 datasets accessible, and of those, only a small number are available. **[1]**

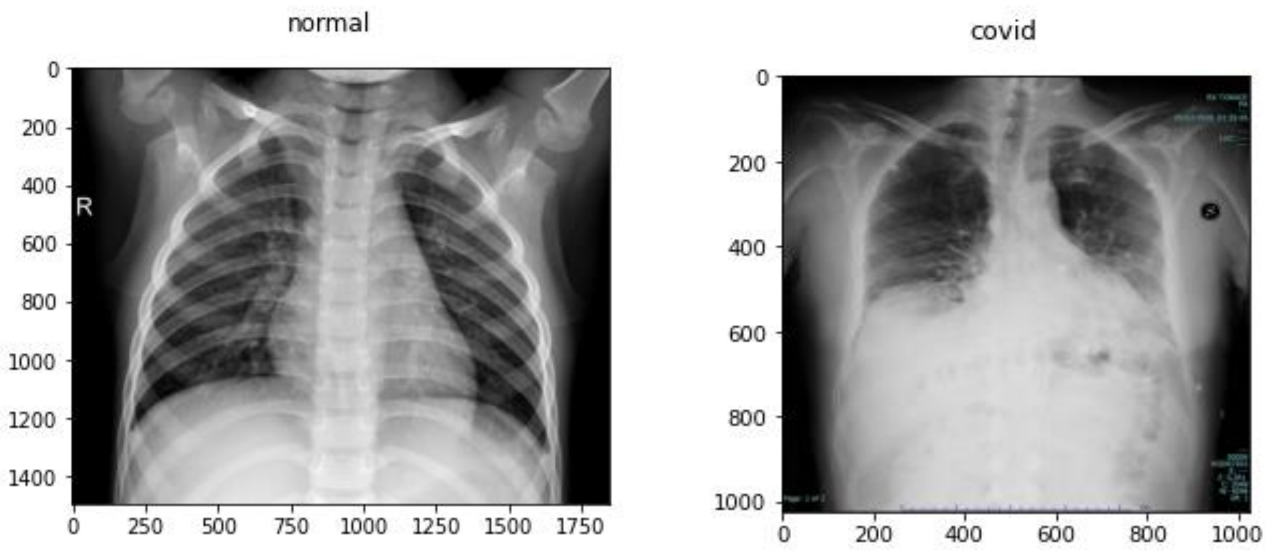

Fig 1.2**:** Normal X-ray & Covid affected X-ray

1.2 Benefits of Covid19 Detection

The results of your COVID-19 test, along with other information, can help your healthcare provider make informed decisions about your care. COVID-19 may help limit the spread of COVID-19 to your family and others in your community**.** Testing plays a key role in our efforts to contain and mitigate the COVID-19 pandemic by identifying infected individuals to help prevent further person-to-person transmission of COVID-19. **[5]**

Every year, vaccines save millions of lives. One of the most important steps in assisting us in returning to doing more of the activities we like with the people we love is the development of safe and effective COVID-19 vaccines. To address some of the most frequent inquiries concerning COVID-19 vaccinations, we've compiled the most recent professional knowledge. Keep coming back because we'll update this post when more details come to light.

(Table 1.1) Top 12 Countries with most confirmed cases of COVID-19.

Country	Confirmed	Confirmed deaths
USA	2,496,628	125,318
Brazil	1,313,667	57,070
Russia	641,156	9,166
India	548,318	16,475
United Kingdom	311,155	43,550
Peru	275,989	9,135
Chili	271,982	5,509
Spain	248,770	28,343
Italy	240,310	34,738
Iran	222,669	10,508
Mexico	212,802	26,381
Pakistan	206,512	4,167

Overfitting must be avoided or minimized since it prevents the CNN from learning the distinctive characteristics of COVID-19 CT images and instead causes it to memorize them. CNN inference demands a lot of computer power, which is another important factor. In actuality, CNNs are often run on extremely costly GPUs outfitted with unique hardware acceleration technologies. However, pricey GPUs are still the exception rather than the rule in widely used computer clusters, which are typically CPU based. (Table 1.1).7 are developing nations, despite the fact that the COVID-19 emergency is also severely stressing the health systems of developed nations. We provide an automated approach for distinguishing between COVID-19 and non-COVID-19 CT scans of the lungs in this study. Its accuracy is on par with sophisticated CNNs, assisted by extensive pre-processing techniques, and it can be run on low- to mid-range machines thanks to its light architecture and great efficiency.

We began by dissecting the Squeeze Net CNN model contrast community-acquired pneumonia and COVID-19 and/or sound CT scans. In fact, Squeeze Net can connect to the accuracy of contemporary CNNs while using fewer parameters. In a recent test, Squeeze Net has furthermore attained the highest degree of accuracy (accuracy divided by number of parameters) and the optimal inference period.

1.3 Artificial-Intelligence

Deep learning-based Artificial Intelligence (AI) solutions are presently employed to solve a variety of biological concerns, such as the detection of breast cancer and brain tumors. It is a member of the machine learning techniques family. Currently, artificial intelligence is being used to automate the diagnosis of a number of diseases, having demonstrated its efficacy and strong performance in automated image categorization challenges using a variety of machine learning approaches. DL is a branch of AI and ML that increases the performance of AI and ML applications. Deep neural networks (DNNs) have been proposed by researchers to aid in the detection of the disease on Chest X-ray images. For the COVID-19 images, Wang and Wong (2020) reported a test accuracy of 92.6 percent, a recall of 96.4 percent, and a precision of 87Percent. **[5]**

1.4 Convolutional Neural Networks (CNN):

The CNN model is used in a number of influential publications to diagnose COVID-19 pneumonia. CNN links. The four essential layers are the convolutional layer, the rectified linear unit (ReLU) activation layer, the subsampling layer, and the fully-connected layer. In addition, CNNs may be trained on datasets of any size by repeatedly iterating over large or small data batches. Other recent improvements include the novel convolutional block attention module (Zhang et al., 2021), data augmentation techniques, new architectures and pre-trained models (He et al., 2016; Nayak et al., 2021), optimization algorithms (Kingmaand Ba, 2014), activation functions (Pedamonti, 2018), regularization techniques such as dropout (Srivastava et al., 2014), and batch normalization. CNNs can be included into limited-capacity devices when their size is appropriate, allowing untrained users to use these devices to identify a range of diseases in undeveloped regions (Rong et al., 2020). The suggested model was trained, validated, and evaluated using retrospective CXIs from real-world patients with COVID-19 pneumonia and other forms of pneumonia. The trained CNN is able to evaluate new photographs by recognizing patterns in each image that indicate to a specific disease. Transfer learning was used to train the neural network to distinguish between normal lungs, COVID-19, and pneumonia. Open datasets from COVID-19, pneumonia, and normal chest X-rays were combined to generate our COVID-19 dataset. It is feasible that the development of a reliable automated COVID-19 detection technology will allow clinicians to receive a second opinion and lessen their workload. **[6]**

1.5 Purpose

We will introduce novel models for COVID19 and other forms of detection using CNNs and chest X-ray images. The two classification scenarios covered by the proposed models are binary classification (COVID-19 vs. Non-COVID) and three-class classification, and they were created to offer accurate diagnoses in more output classes than earlier studies (COVID-19 vs. Normal vs. Pneumonia). Two measures should be done to increase accuracy and avoid overfitting: (1) expanding the data set while balancing classification situations, using data augmentation approaches, and (2) implementing regularization techniques like dropout and automating hyperparameter optimization.

Chapter Two

1. Literature Review

2.1 Background

The goal of this research is to offer a more effective and reliable solution to the present chest illness detection issue. A review of previously planned investigations reveals answers put forth by different writers. Numerous automated methods are employed to address a variety of issues. Many real-time and data science-related solutions, including those for COVID-19, are becoming based on AI systems, Science, technology, health care, industry, education, law enforcement, and marketing all use machine learning (ML) techniques' is a subtype of ML that employs supervised, semi-supervised, or unsupervised methods to process deep neural network data representations A variety of activities relating to medical imaging are carried out using DL approaches .Deep learning can increase the accuracy of X-ray image segmentation in healthcare.

For the purpose of identifying lung abnormalities on chest radiographs and chest tomography, computer-aided detection (CAD) frameworks have been developed and are being applied in the field of chest imaging. COVID-19, which can produce major chest abnormalities and necessitate a multimodal chest detection system for chest illness diagnosis, is found utilizing a CT/X-ray scan of a patient's lungs. **[2]**

The ability of CNN-based techniques to learn mid-level and high-level visual representations has given them increased popularity. The authors of [30] demonstrate how convolutional and DL algorithms may be used to identify various chest diseases in chest X-rays. For the analysis of chest anomalies, several CNNs are introduced. For detecting chest infections, competitive neural networks with an unsupervised learning backend have been developed. Backpropagation neural networks are utilized with the supervised learning backend phenomena. In a few research on multi-class pathological X-ray pictures, COVID-19 must also be taken into account analysis is required of abnormal CT signals, such as those seen in COVID19 patients at our hospitals. Such indicators must support the cognition of these highlights by medical specialists in order for them to make prompt and accurate judgements. Surprisingly, just 56% of COVID-19's initial patients got a standard CT-X-ray examination. However, after the onset of symptoms, CT findings of consolidation, reciprocal and fringe disease, total lung infections, severe opacities, "crazy clearing," and "opposite halo" kinds became more common. A mutual lung connection was discovered. Infected lungs were found in 28% of early patients, 76% of transitional patients, and 88% of late patients. The point of examination was to research chest (CT) images of confirmed COVID-19 patients and to assess their relationship with clinical findings. This study considered80 patients with COVID-19 diagnoses from January to February 2020. The chest CT images and other diagnosed information were reported, and the relation between them was examined .The author presented chest CT discoveries from five patients with COVID-19 infection who had introductory negative, inverted polymerase chain response (RT-PCR) reports. Each of the five patients had regular medical discoveries, including ground-glass opacity, a blended type, and a mixed combination of chest abnormalities.

In order to cover the cost of such hospitalizations, the article in displayed data of patients with chronic obstructive pulmonary disease (COPD) who were admitted for intensive care. Other differentiating characteristics were probably linked to a risk of rehospitalization for severely imperiled patient groupings. Using decision tree analysis, an AI model was utilized to take -into account the factors connected to the risk of rehospitalization. Several publications focusing on multi-class pathological X-rays were subjected to another direct cost analysis from the perspective of public medical insurance.

2.1 (Table 02): Summary of recent studies on the detection of chest-related diseases.

Title of the paper	Tools/Classifier used	Training Image Used	Dataset(s)	Accuracy
Disease Staging and Prognosis in Smokers Using Deep Learning	CNN	1000	-	74.95%
Deep Learning Screening COVID-19	(DL) (ML)		COVID-19 datasets	90.13%
A Deep Neural network to distinguishCOVID-19	CNN	108,948	-	87%
Chest CT manifestation of new coronavirus	GGO	21 patient	--	98%
Chest CT Findings in Coronavirus Disease-19	Ct scan	125 patient	--	88%
Chest disease radiography in twofold: using convolutional neural networks and transfer learning	CNN		Chest x-ray dataset	97%
Pneumonia detection on chest x-ray using machine learning paradigm	ML		Chest x-ray14 dataset	95.8%

2.2 Histology Image Data in Deep learning

Histology is the science of the microscopic nature of organisms' cells and tissues. The word histology" was first used by German anatomist and physiologist Karl Mayer in 1819 in his work " On histology and a new category of tissues of the human body." Pathologists analyze tissue under various magnifications of a microscope slide to spot morphological traits that can be used to diagnose diseases like cancer and Covid-19. Histopathology images can be captured using specialized cameras and a microscope, followed by an automated computerized procedure. The biopsy specimen is embedded [15] in wax and dyed with one or more stains to study the architecture and constituents of tissues under a microscope. Computational pathology goes beyond the simple recognition of morphological patterns, even though the majority of AI research is still concentrated on the detection and grading of tumors and various types of disorders in digital histology and radiology. Implementing AI-based computer-aided medicine combined with clinical data from EHR, including people's clinical risk factors of human- to-human contacts and a variety of different social data, may give quick control of this public health issue with a greater level of quality and safety. Histology images aid in identifying the various types of cell nuclei and their architecture based on a pattern. Histopathologists examine the regularities of cellular architecture and tissue distributions to assess cancerous and other types of disease regions such as-Covid- 19infected lungs, as well as the degree of malignancy. A number of AI businesses are developing products to combat the COVID-19 pandemic. For instance, the polymerase chain reaction (rt chain reaction (RTPCR) results, imaging tests, and Capital by investing Inspection, Korea's (http://www.jlkinspection.com//medical/main) universal AI system, AIHuB, are all being integrated to offer COVID-19 diagnosis. In order to identify and notify patients who are likely COVID19 positive, Persivia, Massachusetts(https://persivia.com/covid-19-detection/), has introduced a new monitoring module based on its Soliton AI engine. An analytical platform called Biovitals Sentinel was created by Biofourmis, a Massachusetts-based company (https://www.biofourmis.com/). It uses histological images based on artificial intelligence to detect early patient deterioration and enable earlier treatments. Machine learning could considerably improve the efficiency and effectiveness of randomized clinical trials for COVID-19, according to Schaaret al., It has the potential to speed up subject recruitment from distinguishable subgroups and subject assignment to treatment or control groups, as well as drastically lower error and need a great deal fewer individuals. Even though machine learning has achieved encouraging results and offers various advantages in computational pathology, the following difficulties must be tackled before deep machine learning may be applied in the clinical setting. Histology is not that difficult to understand; lab experience is required. It requires patience but is not hard. **[15]**

2.3 Limitations and Motivation

A timely diagnosis is essential due to the rapid spread of the coronavirus and the severe effects it has on humans. As mentioned, pneumonia affects a large number of people, especially children, in developing and undeveloped nations with overcrowding, inadequate sanitation, hunger, and a lack of medical care. Early diagnosis is key to curing pneumonia. Autonomous CAD with generalization capability is needed to detect the condition. Most prior strategies in the literature focused on building a single CNN model for pneumonia case categorization, and ensemble learning has not been addressed. COVID-19 results are often inconspicuous. Radiologists can identify 65 percent of positive cases. AI tools may assist mitigate this disadvantage. Doctors will have an X-ray-based early warning tool for COVID-19. CNN's achievements in identifying disease are encouraging, but X-ray-trained models from one hospital or set of hospitals have not been shown to work in other institutions. Current constraints include photo collection biases. If CNN performance predictions are based on CXR test data, they may exaggerate clinical performance. The location of acquisition may be anticipated with great accuracy, both in terms of the CXR equipment used and the hospital department. When creating these models, it's vital to consider that the network may learn the source of the images rather than the disease. Generalization is inversely proportional to the amount of data (images) used to train the algorithm. [17] However, this isn't always the case due to possible biases coming from an imbalance in the numbers of positive and negative images used for training, which are typically of different origin, and the varied features of the images in each set, such as varying toma, pulse width, detection shape, image size, pixel intensity, artifacts, and labels, among others, which, if not handled appropriately, can provide inaccurate findings. Due to the limits of the PCR approach, CNN architectures were examined to overcome this issue. A model for Covid-19 identification was presented that automatically learns characteristics from photos. The proposed model was tested on two publicly available chest X-ray datasets and the Pneumonia Detection Challenge dataset using three-fold cross-validation. The findings outperform state-of-the-art procedures, making the method real-world feasible.As mentioned, pneumonia affects a large number of people, especially children, in developing and undeveloped nations with overcrowding, inadequate sanitation, hunger, and a lack of medical care. Early diagnosis is key to curing pneumonia. Autonomous CAD with generalization capability is needed to detect 20 the condition. Most prior strategies in the literature focused on building a single CNN model for pneumonia case categorization, and ensemble learning has not been addressed. COVID-19 results are often inconspicuous. Radiologists can identify 65 percent of positive cases. AI tools may assist mitigate this disadvantage. Doctors will have an X-ray-based early warning tool for COVID-19. CNN’s achievements in identifying disease are encouraging, but X-ray-trained models from one hospital or set of hospitals have not been shown to work in other institutions. Current constraints include photo collection biases. If CNN performance predictions are based on CXR test data, they may exaggerate clinical performance. The location of acquisition may be anticipated with great accuracy, both in terms of the CXR equipment used and the hospital department. When creating these models, it’s vital to consider that the network may learn the source of the images rather than the disease. Generalization is inversely proportional to the amount of data (images) used to train the algorithm. **[17]**

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2.4 Image processing of Convolutional Neural Network (CNN)

Deep learning algorithms called convolutional neural networks are extremely effective at analyzing images. You will learn how to create, train, and assess convolutional neural networks in this article. This edition includes a new unique network made up of convolution and pooling layers in place of entirely connected hidden layers. CNN operates by detecting characteristics from images. A CNN is made up of the following components:

1. A monochrome image serves as the input layer.

2. The binary or multi-class labels that make up the output layer.

3. Convolution, ReLU (rectified linear unit), pooling, and a fully connected

Neural networks are the components of the hidden layers. Right now, these are the fastest algorithms available for automatically processing images. These algorithms are widely used by businesses to do tasks like item identification in images. [16]

Three Layers of CNN

Image and video recognition applications use convolutional neural networks. The primary applications of CNN are in image analysis tasks including segmentation, object identification, and picture recognition. Convolutional Neural Networks include three different sorts of layers:

1. Convolution Layer.

2. Pooling Layer.

3. Fully Connected Layer.

2.5 Literature Review

According to the literature cited above, X-Ray pictures have been used for the majority of the work. In current history, researchers have started examining and analyzing chest Xray images to discover COVID-19 using deep learning approaches. This research does a thorough analysis of the deep learning techniques that are currently in use for coronavirus infection identification using CXR pictures. Despite the fact that there are additional surveys in the literature, most of them have a larger focus. include AI in computational biology and medicine, data science techniques for pandemic modeling, AI with the Internet of Things (IoT), AI for text mining and natural language processing (NLP), and AI in medical image processing. Ulhaq et al., for instance, reviewed every technique used to combat coronaviruses. This gives a broad overview of what is going on in the world of research. The segmentation of lung images was discussed in a survey, on the use of computer vision techniques for COVID-19. [12] During the process of this research, we might well be able to detect the early stages of lung and heart disease. This paper’s only focus is on deep learning-based coronavirus detection techniques. This publication reviews all approaches mentioned in the literature in the hopes of assisting researchers in developing improved coronavirus detection methods. Three databases may be used to get chest X-ray images: Chest X-ray Images (COVID-19), Chest X-ray Images (Normal), and Chest X-Ray Images (Pneumonia). The model is trained on a small dataset that includes normal (1266), pneumonia (3418), and Covid-19 (460) pictures, as well as test data that includes normal (317), pneumonia (885), and Covid-19 (116) images. [12] Their suggested model's total accuracy is 95.75 percent. The authors also employed deep learning to identify COVID-19 patients from a small number of chest X-ray images, which worked effectively. Employing a few, selected datasets for the study of cell biology to test algorithmic problems. In this work, typical metrics for assessment and comparison are presented together with the techniques, datasets, and utilized datasets. Future directions are also detailed. [18]

CHAPTER THREE

2. Methodology

A framework for the identification of chest disorders, including COVID-19, is put out in this study. In order to diagnose the chest disorders, we first train our suggested 32-layer CNN and use soft-max activations. The fully linked layer of the trained CNN is then subjected to transfer learning. Deep features were retrieved and supplied into ML classification algorithms.

The top performing of the seven machine learning classifiers is then validated 10 times and 5 times. In the first stage of the proposed architecture, a picture is used as input, and preprocessing is then used to normalize the data. Figure illustrates the basic processes in the proposed framework's processing.

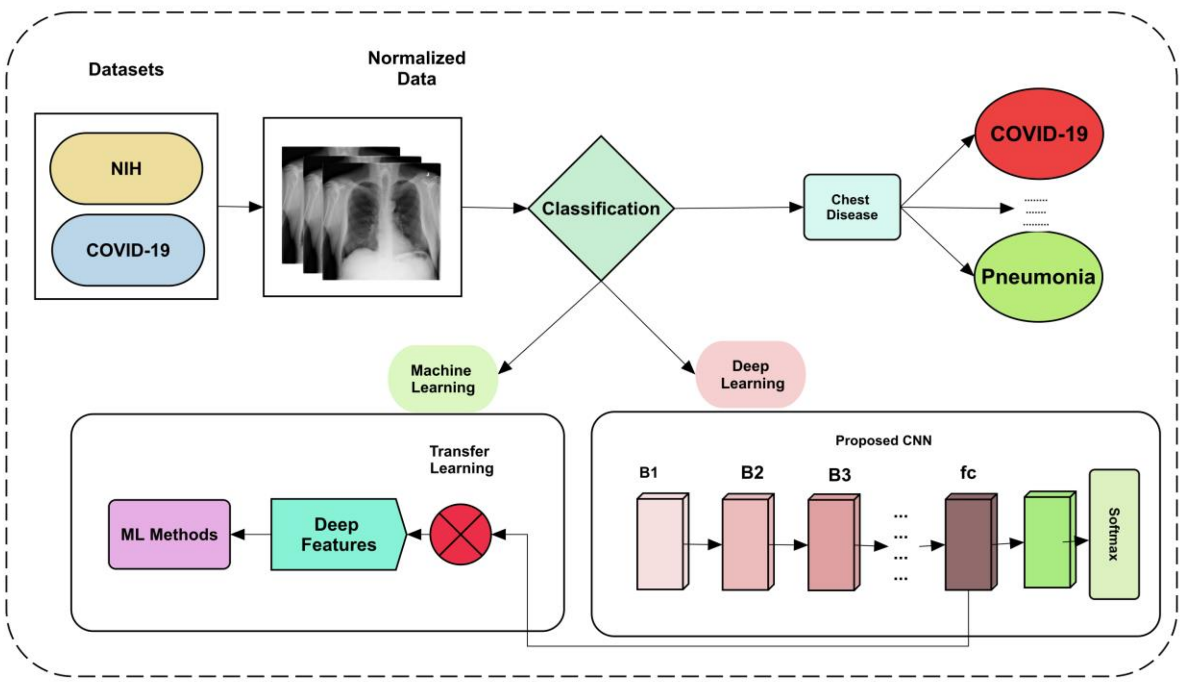


Figure 3.1. The proposed framework contains all steps for classification of chest diseases.

3.1 Dataset

There are numerous datasets used to identify chest disorders, however we chose these two datasets since our suggested approach detects both COVID-19 problems and chest diseases. The NIH and Open COVID-19 X-ray datasets were chosen. To acquire single-unit data, the X-ray modality datasets for COVID-19 and chest disorders were combined. The data were shrunk in a preprocessing phase to normalize it due to the size discrepancy.

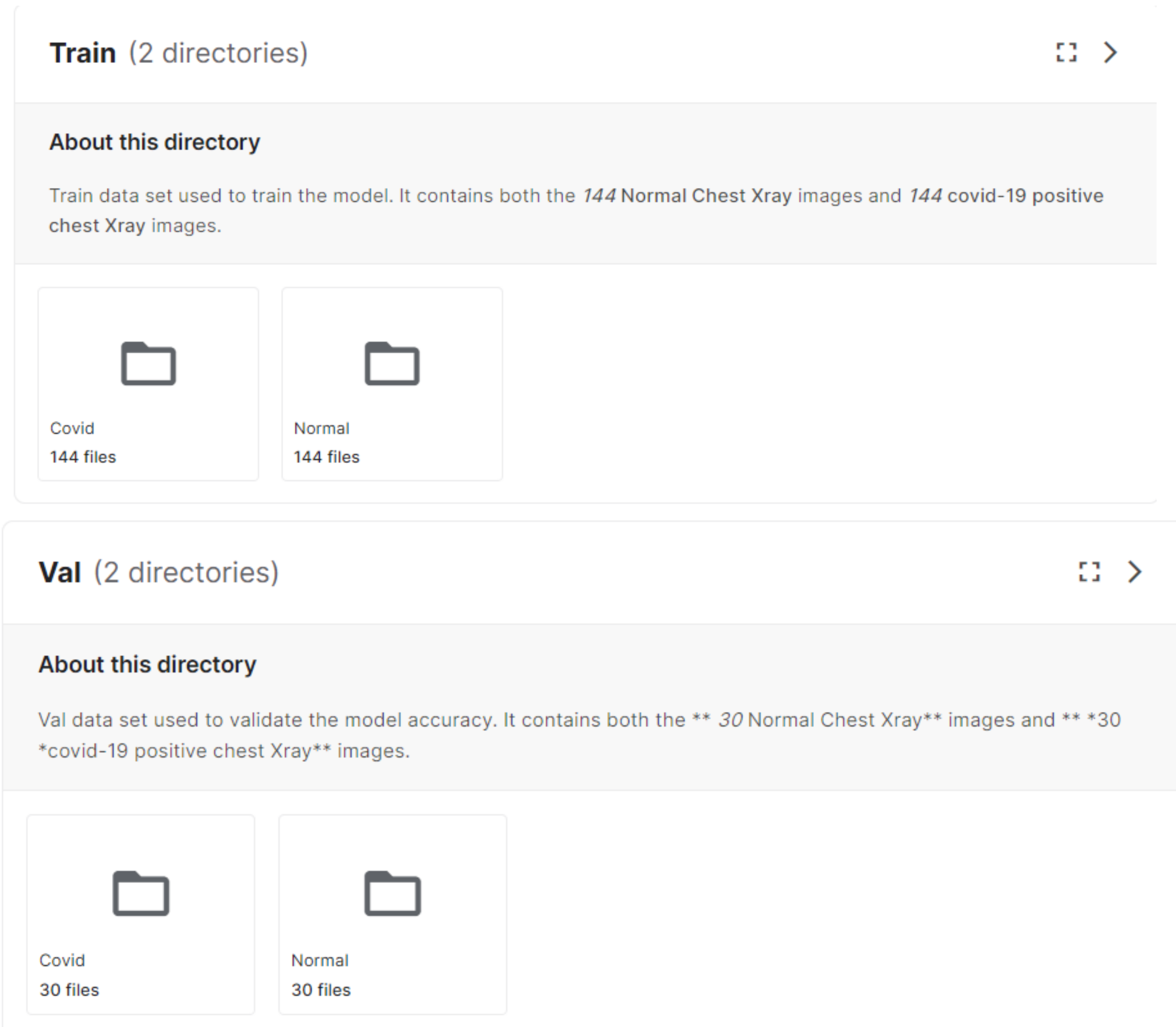
3.2 NIH Chest X-ray Dataset

The updated version of the dataset, which is publicly available and includes six additional illness categories, is used in the current study, which includes a significantly greater number of frontal chest X-ray pictures. In cases when all chest X-ray information settings on clinical sites are still problematic, it was able to get clinically significant information for the identification and diagnosis of CAD systems. However, it is unquestionably possible when several photos are used in a research. This dataset, which makes up 60% of all frontal chest X-rays in the emergency clinic where 14 different chest illness data are included in the proposed study, is distinct from the clinical PACS data based on the National Institute of Health Clinical Center (NIH). [2]

3.3. COVID-19 Chest X-ray Image Dataset

Chest X-rays are an important component of the investigation of COVID-19 infection since they contain clearer picture files. It is necessary to identify many classes of chest diseases, including COVID-19 illness. As a result, the NIH and COVID-19 data that were accessible on Kaggle were gathered and standardized. To prevent overfitting and bias, the number of photos for each class is maintained constant. Table 3.1 displays the normalized photos with the chosen number and dimension.

Table 3.1: Covid-19 chest X-ray image dataset



Datasets	Total image	Size	Classes	Image Format
Covid-19 Chest X-ray image dataset	178+178	1024 × 824	2	JPG & PNG

Train	144+144	1024 × 824	2	JPG & PNG
Validation	30+30	1024 × 824	2	JPG & PNG

3.4 Classification

The proposed study has used two methods of classification for multi-chest disease detection:

(1) the Deep learning and

(2) Machine learning methods. In Deep Learning, the proposed study used a proposed architect of CNN where in Machine learning-based Classification, the transfer learning is applied on proposed CNN fully-connected layer that returns the deep features and then fed them as input data to Machine Learning classifiers.

3.5 Data Preprocessing

The preprocessing stage of the data mining process is crucial. Rubbish in, trash out is a phrase that perfectly describes information mining and AI operations. Data collection methods are frequently approximate, with out-of-bounds values, impossible information combinations, missing attributes, etc. Information is first processed in preparation for main preparation or for further investigation. Data preprocessing is the cycle of organizing unstructured data and fitting it to an AI model. It is the first and most important advancement in strengthening an AI model. Techniques for removing abnormalities and normalizing the data include data cleaning and normalization. It requires a handy structure that can be utilized to create a model. Data redundancy is reduced by the information-based design technique known as normalization. The described normalization rules separate larger tables into smaller tables and connect those utilizing connections. Mathematically, the normalization equation is represented as given in Equation (1):

$$\text{Xnorm} = \frac{x - xmin}{xmax - xmin} \tag{1}$$

where x is the input variable as the individual input, xmin and xmax are the minimum and maximum values from that particular feature, and xnorm is the output of the processed input value. However, the images have pixels that are taken as intensity values. The normalization in these images is somehow different in the context of numeric operations. For this purpose, different interpolation methods have been used in matrix normalization. The data become loss-free when we increase or decrease the input image dimensions. The bilinear interpolation method has been used to preprocess the images. In image processing tasks, the neighborhood pixels are utilized in most cases to obtain focused pixel results. Similarly, in the bilinear method, the 2 × 2 neighborhood operation is utilized to obtain the weighted average. The horizontal and vertical interpolations are performed using corner points of the given input image as points of reference for further operations. Assume the 4 corner points as,

$$C_{(1,1)} = \frac{(\alpha 2 - \alpha)}{(\alpha 2 - \alpha 1)} \quad \frac{(\beta 2 - \beta)}{(\beta 2 - \beta 1)} \, Q1 \tag{2}$$

The vertical corner points C(1,1) and C(2,1) are shown in Equation (2) and (3), where α is the middle point regarding the x-axis between α1 and α2. The middle point is considered as the 2 × 2 neighborhood, where β is taken as the y-axis point, and β1, β2 are the corresponding 2 × 2 neighbors of the middle y point of the considered interpolated point. Q1 and Q2 are the quadrants of the four points of the image.

$$C_{(2,1)} = \frac{\alpha - \alpha 1}{\alpha 2 - \alpha 1} \frac{\beta 2 - \beta}{\beta 21 - \beta 1} \text{ Q2} \qquad (3)$$

Equations (4) and (5) are the corner points of the bottom of a given digital lattice.

These points are shown in Figure.

	$\alpha 1$	α	$\alpha 2$
$\beta 1$	$C_{(1,1)}$		$C_{(1,1)}$
β		P_{final}	
$\beta 2$	$C_{(1,2)}$		$C_{(2,2)}$

Figure**:** Bilinear interpolation method to find the final point (P_final) for the newly interpolated point.

The four corner points with their corresponding 2 × 2 neighbors for the final point calculations have been shown for a better understanding and interpretation of the given equations of the bilinear interpolation method**.**

$$\text{C(1,2)} = \frac{(\alpha 2 - \alpha)}{(\alpha 2 - \alpha 1)} \frac{(\beta - \beta 1)}{(\beta 2 - \beta 1)} \text{ Q3} \qquad (4)$$

$$\text{C(2,2)} = \frac{(\alpha - \alpha 1)}{(\alpha 2 - \alpha 1)} \frac{(\beta - \beta 1)}{(\beta 2 - \beta 1)} \text{ Q4} \qquad (5)$$

As calculated in Equations (2) and (3), by determining the two corner points $C_{(1,2)}$ and $C_{(2,2)}$, the final point Pfinal is calculated by the summation of all of them, as given in Equation (6).

$$P_{final} = C_{(1,1)} + C_{(2,1)} + C_{(1,2)} + C_{(2,2)} \qquad (6)$$

3.6 Proposed CNN

CNN stands for Convolutional Neural Network, a specific neural network for handling information that has a 2D input shape. CNNs are ordinarily utilized for image detection and classification. In this stage, we train our CNN. The proposed CNN is based on a 32-layer architecture. The size of input images is set 1024 × 1024. The images are fed to Convolutional Blocks where our convolutional blocks include a sequence of 4 layers (Convolution, batch-normalization, ReLU, and Max-Pooling) with different parameters as explained in Table 2. For our first Convolutional Block, we make a window of 3 × 3 and convolve the image through kernels, where number of filters is set to 16 and these number of filters increases by incoming convolutional layers. The layer-by-layer visualization of weights is shown in Figure 3. After the convolution layer, we then apply batch normalization. Batch normalizations a strategy for preparing deep neural networks that normalizes inputs to a layer for every scaled-down bunch. This settles the learning process and reduces data variation. Let us have a look on CNN layers that how they work individually.

3.7 Convolutional Layer

The convolution layer contains at least one convolutional operation. For the first convolutional layer, the kernel size is 3 × 3 with equal padding. The output tensor and the input tensor have the same width and height. The tensor flow will add zeros in the row sand columns to ensure the same size. Convolutional blocks indicate how many times the image is iterated over 4 layers in proposed study. Our convolutional layer output size is (N − m + 1) × (N − m + 1). The output of the 1th convolution layer, denoted as in consists of feature maps. It is computed as shown in Equation (7):

$$C_i^{(l)} = = B_i^{(l)} + a \sum_{j=1}^{a_1(l-1)} k_{i.j}^{l-1} \times C_i^{l} \qquad (7)$$

Where B_i^l is the bias matrix and the convolution filter or kernel of size a × a that connects the j-th feature map in layer (l − 1) with the i-th feature map in the same layer. The out-put layer consists of feature maps. The first convolutional layer has input space. Our first convolutional block is 3 × 3, and the number of filters used is 16.

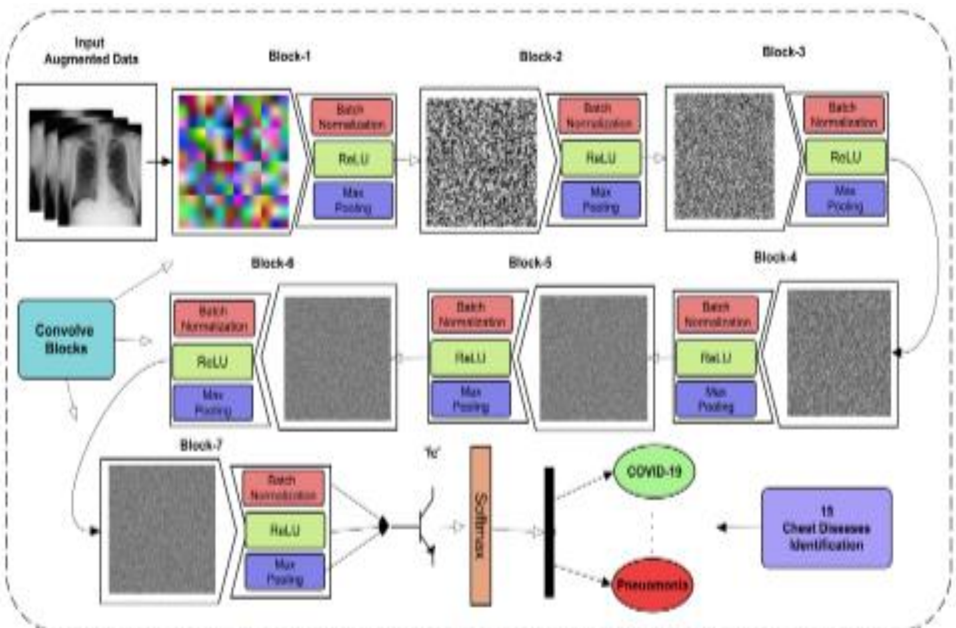


Figure 3.2: Proposed CNN design with convolve layer weight activation.

3.8 Max Pooling Layer

Max pooling computation is the next step. The pooling counting will reduce the addition of the data. In this stage, the module max-pooling2D with a size of 3 × 3 and a stride of 2 is used. For a pooling layer, one can specify only the filter/kernel size (F) and the strides (S).

$$\text{Pooling Output dimension} = [(I - F) / S] + 1 \times D \tag{9}$$

There is no special parameter in the pooling layer, but it has two hyperparameters: Filter(F) and Stride(S). In general, if we have input dimensions of W1 × H1 × D1, Then, [7]

$$W2 = (W1 - F) / S + 1 \tag{10}$$

The kernel or operational window is represented as W; the window that is needed to compute, represented as W1; and the result is shown as W2. The number of filters in the proposed CNN is changed in each block in the convolutional layers, where the max- pooling filter window size remains the same at 2 × 2 with a stride of 1. The image is then downsampled to max-pooled data that are further processed by the subsequent layers.

$$H2 = ((H1 - F)/S + 1-F) \tag{11}$$

In Equation (11), F is the spatial extent in the given filter of the image, and H is the height of the given image. These are the columns of the image. However, their height is calculated as stride by subtracting the assigned corresponding number of filters with their 3 × 3 size. This is later on subtracted from the stride with a summation of 1 by subtracting it from the spatial extent,

$$D2 = D1 \tag{12}$$

If the volume of an input image is W1 × H1 × D1, then an output of size W1 × H1 × D1 is produced by a pooling layer. The equations for W2, H2, and D2 in the pooling layer are shown above, where W2, H2, and D2 are the width, height, and depth of the output, respectively.

Max pooling is most favorite pooling layer in CNN. Basically, it implies the biggest value and put to the output. The output will be biggest number correspondingly different color shaded region. Each region will get one output. In figure 3.3, there are 4×4 matrix and uses 2×2 pooling layer. So, the output size will be 2×2. In input layer, there are divided 4 different regions. Each of the region have 4 different number. In max pooling, we collect large value. Then we put it in the output matrix.

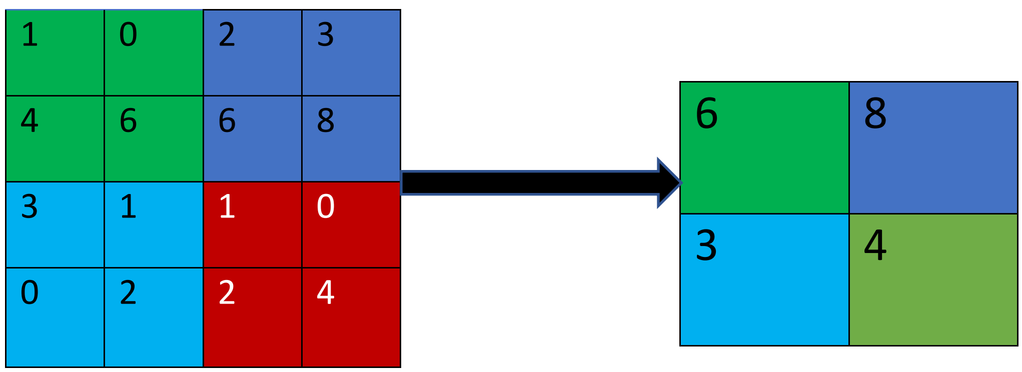


Figure 3.3: Max Pooling Layer

3.9 Average Pooling Layer

It is second most used pooling in CNN. Basically, it implies the average of all value and put to the output. The output will be average number correspondingly different color shaded region. Each region will get one output. In figure 3.4, there are 4×4 matrix and uses 2×2 pooling layer. So, the output size will be 2×2. In input layer, there are divided 4 different regions. Each of the region have 4 different number. In average pooling, those number are calculated and get the average number. Then we put it in the output matrix.

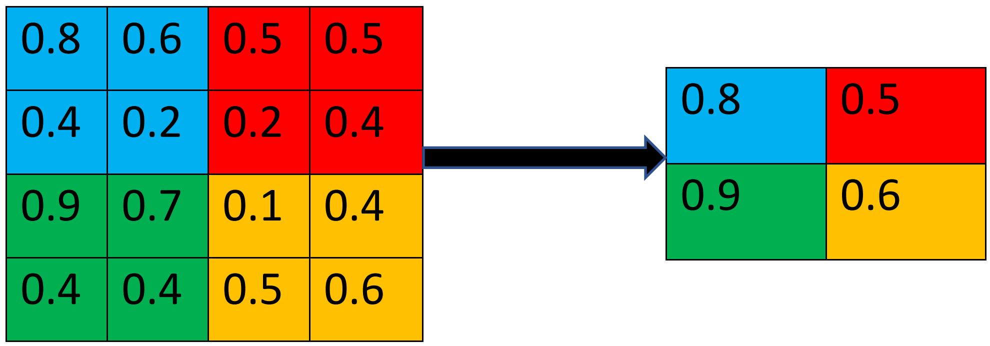


Fig 3.4: Average Pooling Layer

3.10 Rectified Linear Unit (ReLU)

ReLU refers to the Rectifier Unit, the most ordinarily conveyed initiation work for the output of CNN neurons. Unfortunately, ReLU work is not differentiable at the beginning, which makes it difficult to use with backpropagation preparation. In this layer, we eliminate low values from the sifted picture and supplant it with nothing. This capacity is possibly enacted when the hub input is over a specific amount. Thus, when the info is under zero, the yield is zero.

$$f(x) = \max(0, x) \text{ where } x = \text{input value} \qquad (13)$$

Therefore, to cover any in-bounding and out-bounding range of pixels, the activation function is performed, and this normalizes incoming values.

3.11 SoftMax Layer

Softmax is a numerical capacity that changes over a vector of numbers into a vector of probabilities, where the probabilities of each value correspond to the general size of each value in the vector. Convolutional layers are layers where channels are applied to the first picture, or to other element maps in a deep CNN. We use 29 layers for training.

3.12 Convolutional Neural Network Architecture

The Convolutional Net's task is to compress the images into a more manageable format while maintaining components that are crucial for getting a good prediction. This is crucial for creating an architecture that can learn features and scale to enormous datasets. [11] Three

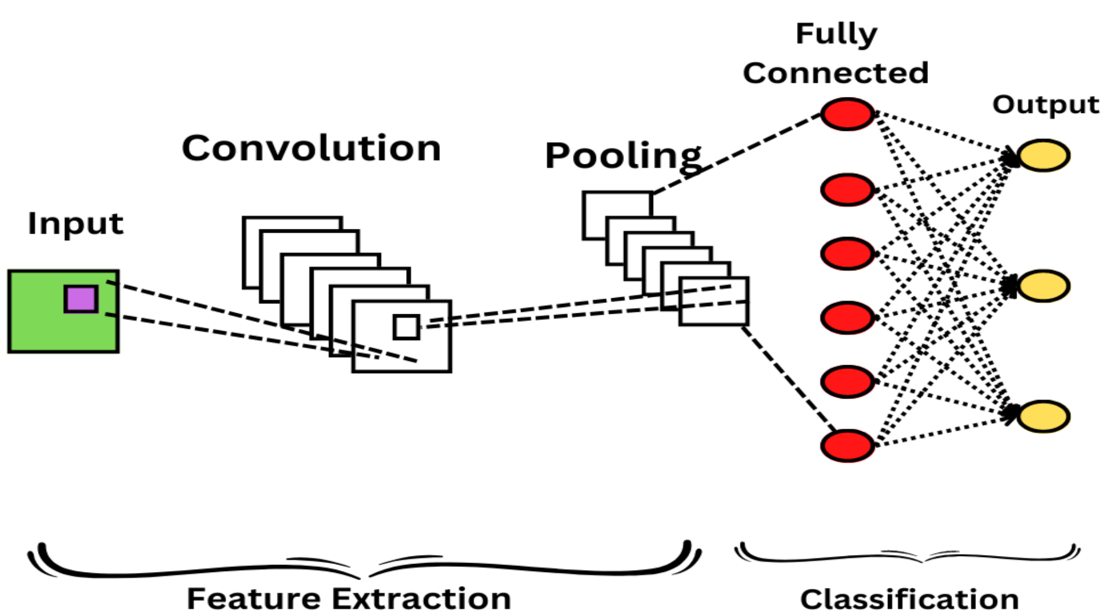


Figure 3.5: A convolutional neural network

layers make up a convolutional neural network, or Convolutional Networks in short. Let's take a closerlook:

3.13 What Is a Convolution?

Convolution is an orderly procedure where two sources of information are intertwined; it's an operation that changes a function into something else. Convolutions have been used fora long time typically in image processing to blur and sharpen images, but also to perform other operations. (e.g. enhance edges and emboss) CNNs enforce a local connectivity pattern between neurons of adjacent layers. CNNs make use of filters (also known as kernels), to detect what features, such as edges, are present throughout an image. There-are four main operations in a CNN:

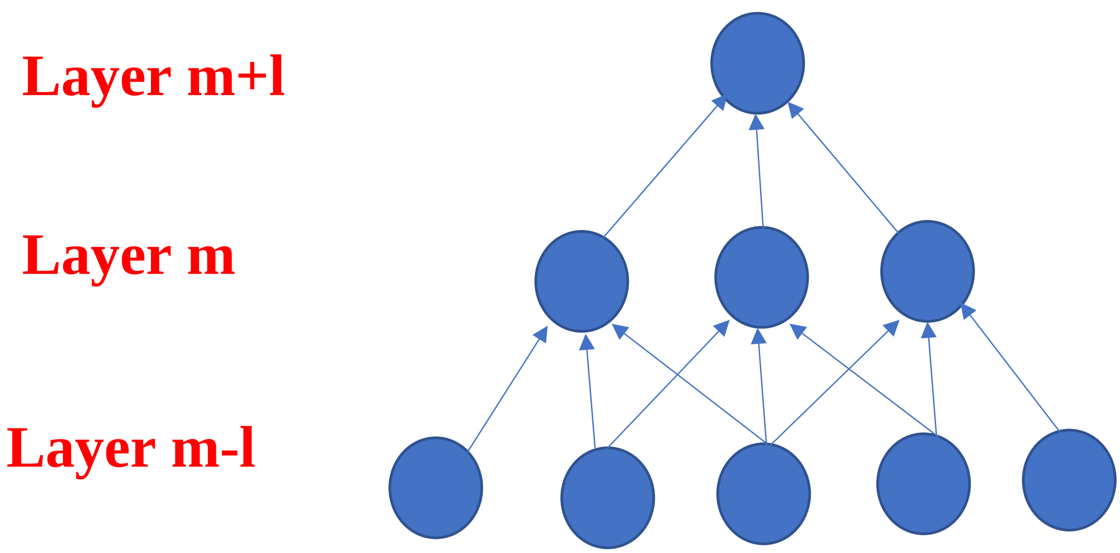


Figure 3.6: A demo CNN layer.

3.14 Proposed Convolutional Neural Network

A convolutional neural network (CNN) is a form of artificial neural network that is specifically made to process pixel input and is used in image recognition and processing. CNNsare effective artificial intelligence (AI) systems for image processing that employ deep learning to carry out both generative and descriptive tasks. They frequently use machinevision, which includes image and video identification, recommender systems, and naturallanguage processing (NLP). A hardware or software system known as a neural network is modeled after how neurons in the human brain function. Traditional neural networks must be fed images in pixel-by-pixel, low-resolution chunks, which is not suitable for image processing. CNN's ”neurons” are set up more like the frontal lobe, which in hu- mans and other animals is where visual data are processed. The full visual field is coveredby the layers of neurons, overcoming the issue with standard neural networks' piecemealpicture processing. A multilayer perceptron-like system that has been optimized for low processing demands is used by a CNN. An input layer, an output layer, and a hidden layerwith several convolutional layers, pooling layers, fully connected layers, and normalizinglayers make up a CNN's layers. A system that is significantly more effective and easier to train for image processing and natural language processing is produced by the removalof restrictions and increase in efficiency for image processing.

3.15 Fully Connected Layer (FC)

The flattened input used by the fully connected layer (FC) means that each input is tied toeach neuron. The flattened vector is then transmitted via a few more FC layers, where theusual mathematical functional operations are carried out. At this moment, the classification process begins. If FC layers are present, they are often located near the end of CNN architectures.

What is Fully Connected Layer?

1. A layer of an artificial neural networks where each element of the layer is connected to each element of the following layer. Learn more in: Enhanced Footsteps Generation Method for Walking Robots Based on Convolutional Neural Networks

2. A network layer where all neurons of the layer are connected to all neurons of the previous layer. Learn more in: Convolutional Neural Network

3. A network layer where all neurons of the layer are connected to all neurons of the previous layer. Learn more in: Deep Learning on Edge: Challenges and Trends.

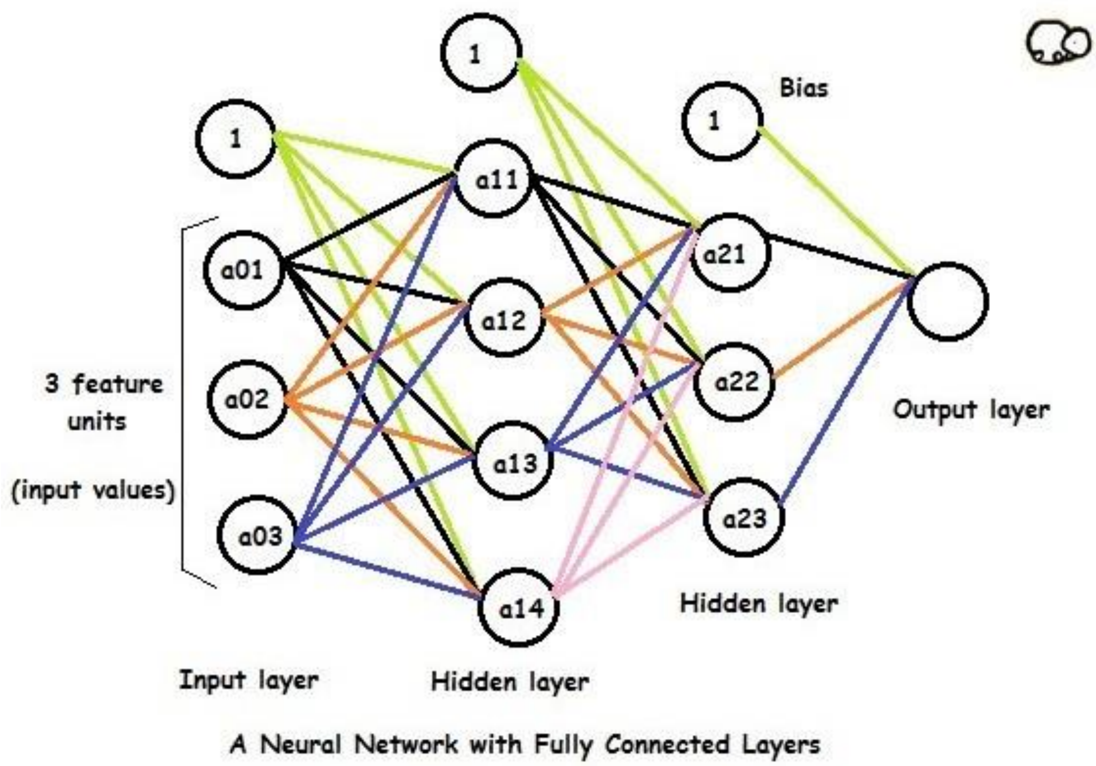


Figure 3.7 : Fully Connected Layer.

3.16 Activation Functions

An activation function in a neural network describes how a node or nodes in a layer of thenetwork translate the weighted sum of the input into an output. A ”transfer function” is another name for the activation function. It may be referred to as a ”squashing function” ifthe output range of the activation function is constrained. Numerous activation functions have nonlinear behavior, which is referred to as “nonlinearity” in network or layer design.Different activation functions may be used in different regions of the model, and the choice of activation function has a significant impact on the neural network’s capacity and performance. Although networks are built to utilize the same activation function for all nodes in a layer, technically the activation function is applied before or after the internal

processing of each node in the network. A network may have three different kinds of layers: output levels that produce predictions, hidden layers that receive data from one layer and transfer it to another, and input layers that take raw input directly fromthe domain. Typically, the same activation function is used by all buried levels. The sortof prediction needed by the model will determine what activation function is used in the output layer, which is often different from the hidden layers. The activation function is applied before or after each node in the network’s internal processing, despite the fact thatnetworks are designed to use the same activation function for all nodes in a layer. Three different layers can exist in a network: input layers that receive raw data from the domain,hidden layers that accept data from one layer and pass it to another, and output levels that provide predictions. All buried levels typically employ the same activation function. Theactivation function employed in the output layer, which is frequently different from the hidden layers, will depend on the type of prediction required by the model.

3.17 Dropout layer

A Dropout layer is another prominent feature of CNNs. The Dropout layer acts as a mask, eliminating some neurons' contributions to the subsequent layer while maintaining the functionality of all other neurons. If we apply a Dropout layer to the input vector, some of it features are eliminated; however, if we apply it to a hidden layer, some hiddenneurons are eliminated. **[8]**

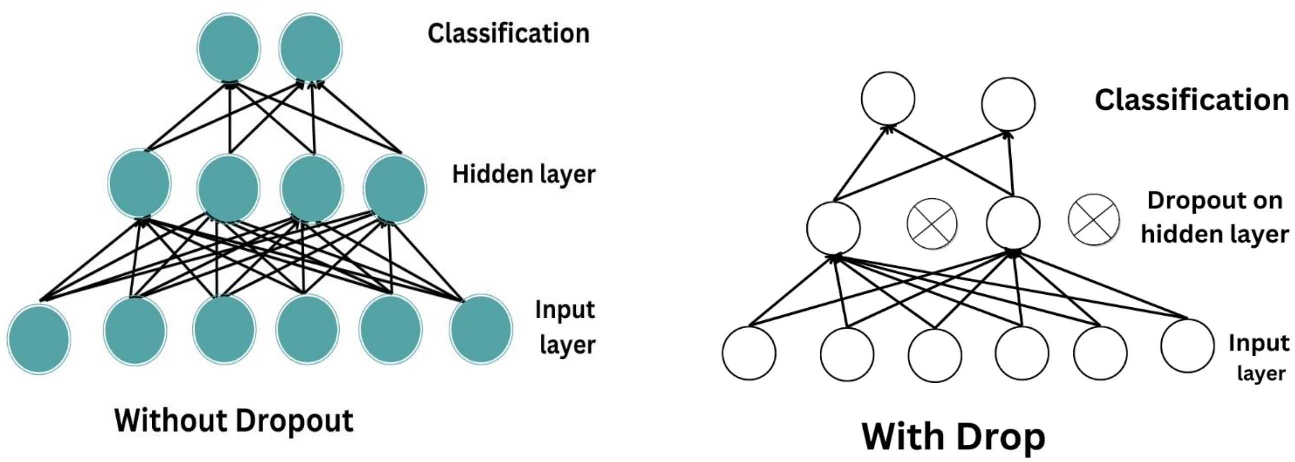


Figure 3.8: Dropout Layer

3.18 Backpropagation

The foundation of neural network training is backpropagation. It is a technique for adjusting a neural network's weights based on the error rate recorded in the previous epoch (i.e.,iteration). By properly tweaking the weights, you may lower error rates and improve the model's reliability by broadening its applicability. The term "backward propagation of errors" is shortened to "backpropagation" in neural networks. It is a common technique for developing artificial neural networks. With regard to each weight in the network, thistechnique aids in calculating the gradient of a loss function.

How Backpropagation Algorithm Works?

The gradient of the loss function for a single weight is calculated by the neural net- work's back propagation algorithm using the chain rule. In contrast to a native direct calculation, it efficiently computes one layer at a time. Although it computes the gradient, it does not specify how the gradient should be applied. It broadens the scope of the delta rule's computation. Consider the following Back propagation neural network example diagram to understand.

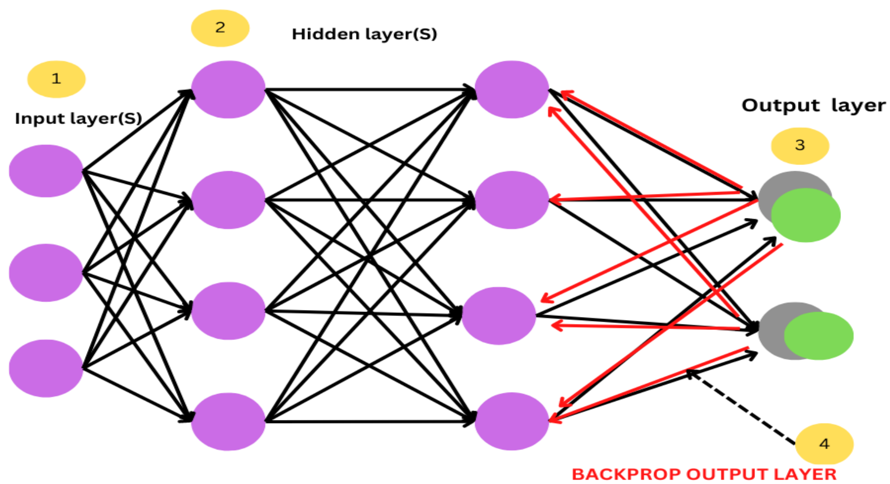


Figure 3.9: Backpropagation Dropout Layer

3.19 Alex Net Model

Alex Net, a convolutional neural network was introduced by Alex Kievsky and his team in 2012. It is broaderand deeper than the Linnet model and successful against hard ImageNet challenges to detect the objects and recognize it. The discovery of Alex Net brought breakthroughs in the area of machine learning. The architecture of Alex Net is **depicted.** To perform max pooling and convolution, the first convolutional layer use 96filters and the size of the filters are 11*11. The max pooling is accomplished with 3*3 filters where a size of 2 stride is used as well. In the second layer, the same operations accomplished with 5*5 filters. In terms of the 3rd, 4th and 5th convolutional layers, 384, 384 and 296 featured maps are used respectively with 3*3 filters. Relu is the activation function is used here. With the dropout, 2 fully connected layers are also used with a SoftMax activation function at the end. In this architecture, two networks with comparable structures are trained along withthe same number of featured maps. The model introduced two new concepts of machine learning and they are Local Response Normalization (LRN) and dropout. LRN can be implemented in two different ways. The first way of LRN applies on the feature map or single channel and it has an N*N patch that is chosen from the featuremaps. [13]

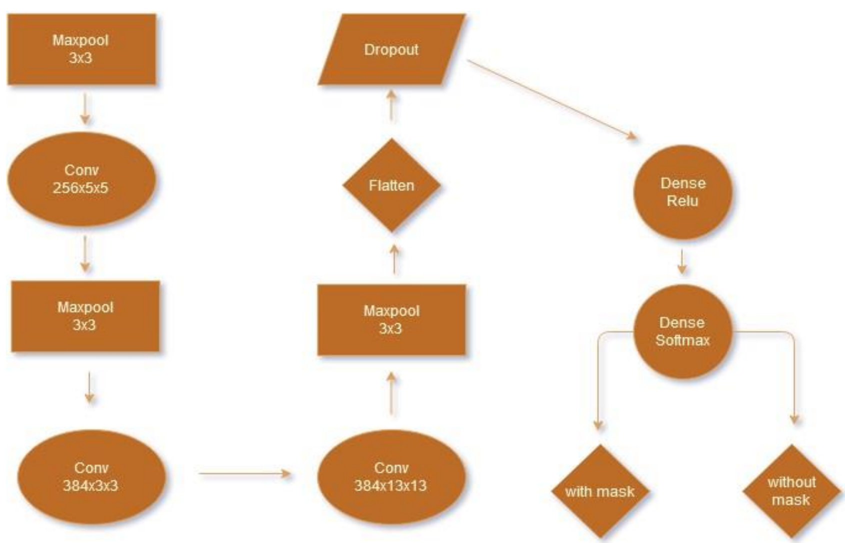


Fig 3.10 Alex Net architecture

Layer	Filter Number and size	Size of feature map
Conv Stride 4	96 11x11	55x55x96
Max Pool Stride 2	3x3	27x27x96
Conv 2 Stride 1, padding 2	256 5x5	27x27x256
Max Pool Stride 2	3x3	13x13x256
Conv 3 Stride 1, padding 1	384 3x3	13x13x384
Conv 4 Stride 1, padding 1	384 3x3	13x13x384
Max pool Stride 2	3x3	6x6x256
Dropout Layer		6x6x6256

Table 3.2: Alex Net Model

3.20 Mobile Net V2

In real-world applications, Mobile Nets are a CNN design that is both efficient and portable. Mobile Nets are CNNsthat can fit on a mobile device and classify photographs or detect objects with low latency. They're usually relatively small CNN architectures, which makes them easy to run in real time on embedded devices like smartphones and drones. The approach has been tested on CNNs with 100-300 layers and has outperformed alternative architectures like VGG Net. In real-world instances of Mobile Nets CNN architecture, CNNs embedded in Android phones run Google's Mobile Vision API, which can automatically recognize labels of popular things in images. **[20]** MobileNetV2 is a sophisticated image classification software. MobileNetV2, a lightweight CNN-based deep learning model, uses TensorFlow to give picture weights. The MobileNetV2 foundation layer is removed first, followed by the addition of a new trainable layer. Our photographs are analyzed by the model, which extracts the most important aspects. In MobileNetV2 [34], there are 19 bottleneck layers. We chose OpenCV as the foundationmodel, which is built on the ResNet-10 architecture **[19].** OpenCV's Caffe model is used to detect the face and mask from a picture and a video stream. The result face recognized image is sent to the mask detecting classifier.It makes mask detection in video streaming faster and more precise. Overfitting is a common problem in machinelearning. Our model was overfitted with the dataset, thus the Dropout layer was utilized to ignore it. We were able to do away with the base layer by using MobileNetV2 (include top=False). Resized images In our trainablemodel, we apply an average pooling procedure with 128 hidden layers .Relu is utilized in the secret layer, and SoftMax is used across the linked layer. We used a learning rate of 0.01 to improve accuracy. The Adam stochastic gradient descent approach helps the model understand visual features.

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1 Conv / s1	$3 \times 3 \times 512$ dw $1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$ $14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Table 3.3: MobileNetV2 Architecture

3.21 VGG-16

VGG-16 is another transfer learning and deep learning model. Simonian and Zisserman created this network. The architectural design is made up of back-to-back convolutional layers. Following that, a max-pooling layer is added. Then there are two convolutional layers that are back-to-back, followed by a max-pooling layer. Following that, three convolutional layers are added, followed by a pooling layer. Following that are three convolutional layers, followed by a max-pooling layer that is repeated twice. The structure is finished with three thick layers. The final of these dense layers is the output layer, which contains three neurons and represents the three classes of our classification job.

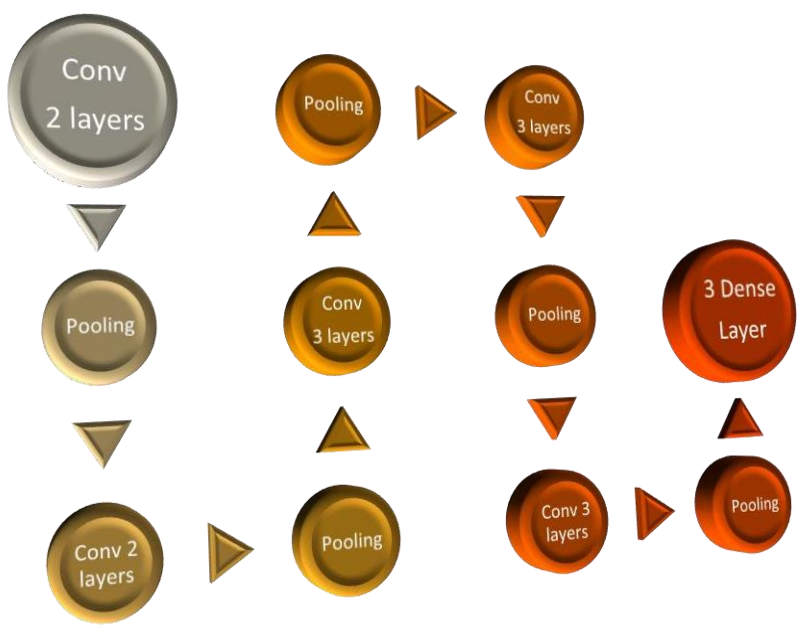


Fig 3.11: VGG16 architectural layers

Layers	Size and dimension
First 2 convolutionlayer. Stride 1 Padding 1 64 channels	Kernel3x3 (224x224x64)
Max Pooling Stride 2	2x2 112x112x64
3,4 convolution layers 128 channels	Kernel 3x3 112x112x128
Max Pooling Stride 2	2x2 56x56x128
5,6,7 Convolution	3x3 kernel 56x56x256
max Pooling stride 2	2x2 28x28x256
8,9,10 convolution	3x3 kernel 28x28x512
Max pooling Stride 2	2x2 14x14x512
11,12,13	3x3 kernel
Convolution Max Pooling Stride 2	14x14x512 2x2 7x7x512

Table 3.4: VGG16 Model

3.22 Keras

Google developed Keras, a high-level deep learning API for building neural networks. It is made in Python and facilitates the development of neural networks. It is quick, simple, and modular. It was made by Google developer Francois Chollet. Keras cannot handle computation at the lowest level. Instead, it makes use of a "Backend" library. You can swap between various back ends with Keras. Several frameworks are supported by Keras including as TensorFlow, Flask etc. **[21]**

Chapter Four

4. Result & Analysis

4.1 Deep Learning

Machine Learning is a subset of Artificial Intelligence, while Deep Learning is a subset of Machine Learning [9]. Deep learning tries to emulate the human brain, but it falls well short of its capabilities. It enables systems to cluster data and produce extremely accurate predictions. Deep learning is a machine learning technique that teaches computers to perform what people do naturally. It is inspired by the anatomy of the human brain. Deep learning is receiving a lot of attention these days, and for good reason. It's accomplishing accomplishments that were previously unattainable When we think of deep learning, the name "Neural Network" comes to mind first because it is such a vital component. Neural networks use a set of algorithms to simulate the human brain. Deep learning algorithm analyze data with a logical structure in order to reach conclusions that are comparable to those reached by humans. Deep -learning achieves this by employing a multi-layered computational structure known as a neural network. The neural network's design is primarily inspired by the structure of the human brain. We use our brains to identify styles and classify different pieces of information, and neural networks can be trained to do the same thing with data. Separate layers of neural networks can also be thought of as a type of filter that works from the most extreme to the most extreme, increasing the possibility of detecting and producing an accurate result. We use neural networks to group and classify things. We can use neural networks to group or sort unlabeled data based on similarities between the samples in the data, or we can train the network on a labeled dataset to categorize the samples in the dataset into various categories. Deep neural networks can thus be considered components of broader machine learning programs involving reinforcement learning, classification, and regression methods. [9]

Deep learning and artificial neural networks are extremely powerful and unique in today's market. The fundamental advantage of deep learning over machine learning is the absence of the need for so-called feature extraction. Long before deep learning, flat machine learning techniques like Decision Trees, SVM, Nave Bayes Classifier, and Logistic Regression were used. Normally, these techniques can't be used to raw data like.csv files, images, or text. Feature Extraction, a preprocessing step, is necessary. Feature extraction is typically challenging and requires a deep understanding of the problem domain. The feature extraction process is not necessary for Deep Learning Artificial Neural Networks. The layers can directly and independently learn an implicit representation of the raw input. To conduct and optimize the feature extraction process, deep learning models require little to no manual work. While deep learning was first proposed in the 1980s, it has only lately become relevant for two reasons:

• Deep learning necessitates a large amount of labeled data. For example, the creation of self-driving cars involves millions of photos and thousands of hours of video.

• Deep learning necessitates a significant amount of computing power. The parallel design of high- performance GPUs is ideal for deep learning. This helps development teams reduce deep learning network training time from weeks to hours or less when used in conjunction with clusters or cloud computing.

4.2 How deep learning works:

Most deep learning approaches use neural network topologies, deep learning models are sometimes referred to as deep neural networks. The term "deep" refers to the amounts of hidden layers in a neural network. Traditional neural networks have only 2-3 hidden layers, however deep neural networks can have up to 150. Deep learning models are trained using large quantities of labeled data and neural network topologies that learn features directly from the data without the need for manual feature extraction. Neural networks are made up of layers of nodes, similar to how the human brain is made up of neurons. The deep learning model consists of an input layer, one or more hidden layers, and an output layer.

Input Layer: Input nodes are used to represent all of the input variables. In the artificial neural network's workflow, the input layer is the first phase. After receiving data as input, the computer converts it to bits of binary data so that it can interpret and actualize the information. To be within the same range, input data variables must be either standardized or normalized.

Hidden Layer(s): In the hidden layer, all of the input variables are aggregated across one or more nodes. This essentially adds new features based on the provided inputs. In most cases, all input nodes are connected to all hidden layer nodes. We're now dealing with deep learning if our neural network contains more than one hidden layer. The non-linear processing units for feature extraction and transformation are performed by the layers here. It gradually develops the hierarchy concepts through learning. Each step of the hierarchy transforms the input data into a more theoretical and composite representation.

Output Layer: A prediction or classification is made in the output layer utilizing the nodes in the hidden layer. One output node is used for numerical prediction. C-1 nodes are used for classification, where C is the number of classes that can be created. The activation function transforms the integrated weighted input from the node into the node's activation function in a neural network output layer. Two of the most effective activation functions are relu and sigmoid. It's because the model Relu employs is simpler to train and capable of generating superior results. For each layer, we'll additionally see a Bias Node. A bias node works in the same way as a regression intercept.

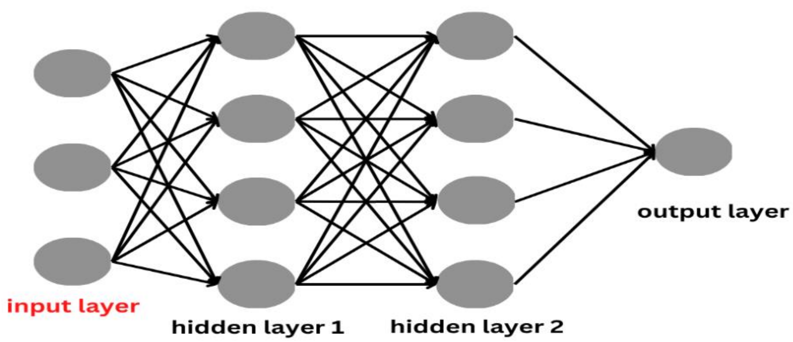


Figure 4.1: Deep learning architecture

4.3 Experimental Result & Analysis: The result section includes the train-test accuracy, confusion matrix, classification report for each of the used models.

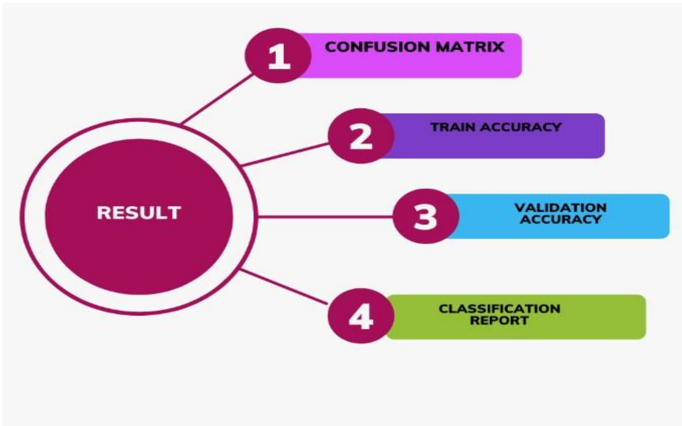


Fig 4.2 Parts of Result

Here, we used the deep learning architecture as a model for our own CNN design. Four convolutional layers, four max pooling layers, three dropout layers, and two thick layers are used in this architecture. In this architecture, each epoch has 50 steps epoch size. By doing this, we are attempting to guarantee that our accuracy must be between 98% and 100%. We reached our goal, and we were successful. Our accuracy rate is greater than 97%. This is admirable for a new architecture. **[10]**

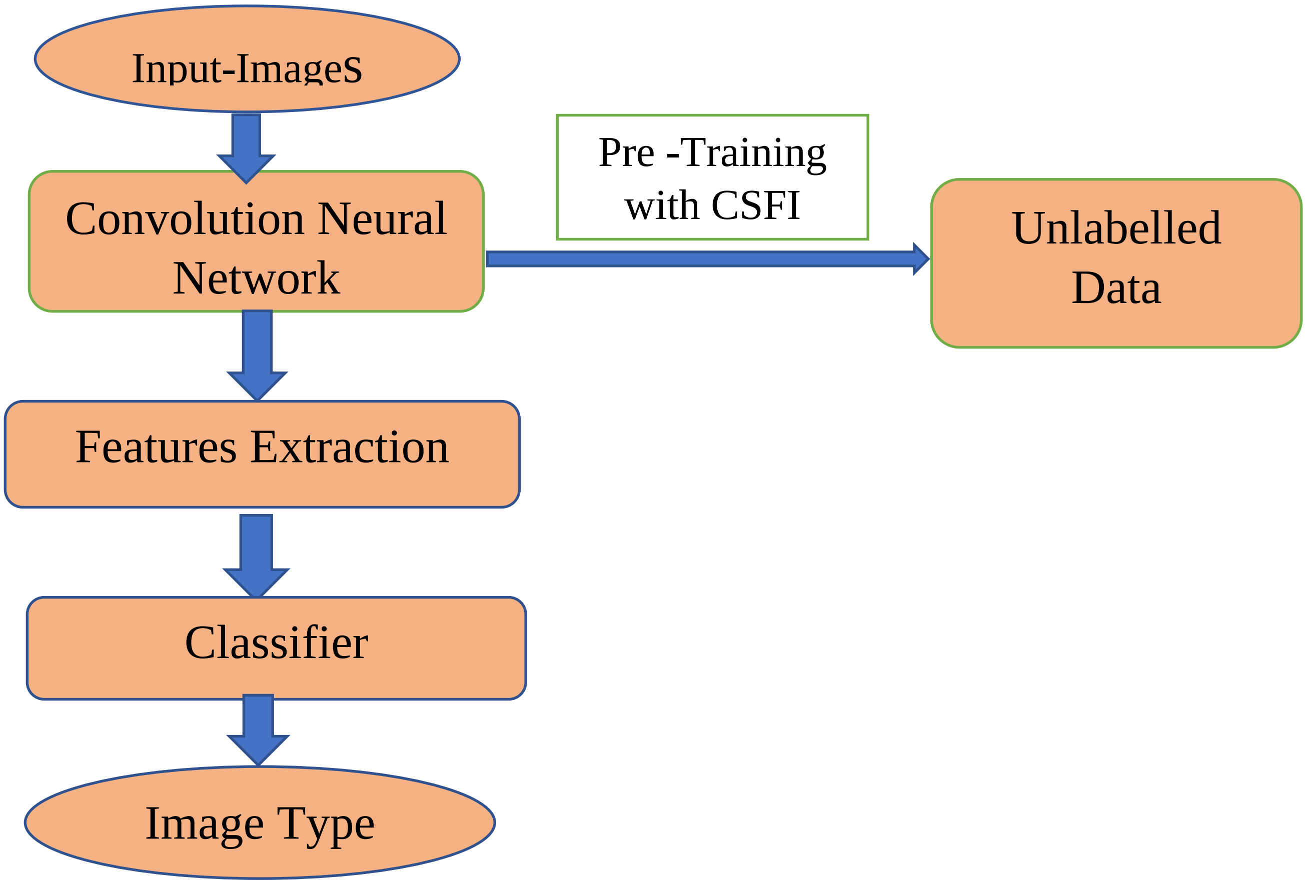


Figure 4.3: CNN Architecture Flowchart

TABLE 4.1: Details about the proposed CNN layers.

Number	Layer Names	Activations	Kernel Size	Stride	Parameters	Feature Maps
1	Input layer	180 × 180 × 3	/	180 × 180	/	/
2	Convolutional layer (C1)	180 × 180 × 3	3 × 3	/	Weights = 3 × 3 × 3 × 32 Bias = 1 × 1 × 32	32
3	ReLU (R1)	178 × 178 × 32	/	/	/	/
4	Maximum pooling layer (MP1)	178 × 178 × 32	2 × 2	2	/	/

5	Convolutional layer (C2)	178 × 178 × 32	3 × 3	1	Weights = 3 × 3 × 16 × 64 Bias = 1 × 1 × 64	64
6	ReLU (R2)	87 × 87 × 64	/	/	/	/
7	Maximum pooling layer (MP2)	87 × 87 × 64	2 × 2	/	/	/
8	Convolutional layer (C3)	87 × 87 × 128	3 × 3	/	Weights = 3 × 3 × 32 × 128 Bias = 1 × 1 × 128	128
9	ReLU (R3)	41× 41 × 128	/	/	/	/
10	Maximum pooling layer (MP3)	41× 41 × 128	2 × 2	/	/	/
11	Convolutional layer (C4)	41× 41 × 128	3 × 3	/	Weights = 3 × 3 × 64 × 128 Bias = 1 × 1 × 128	128
12	ReLU (R4)	39 × 39 × 128	/	/	/	/
13	Dropout_1	39 × 39 × 128	/	/	/	/
14	Convolutional layer (C5)	39× 39 × 128	3 × 3	/	Weights = 3 × 3 × 128 ×128 Bias = 1 × 1 × 128	128
15	ReLU (R5)	37 × 37 × 128	/	/	/	/
16	Average pooling layer (MP5)	37 × 37 × 128	2 × 2	/	/	/
17	Convolutional layer (C6)	37× 37 × 256	3 × 3	/	Weights = 3 × 3 × 128 × 256 Bias = 1 × 1 × 256	256
18	ReLU (R6)	32 × 32 × 256	/	/	/	/
19	Dropout_2	32 × 32 × 256				

20	Average pooling layer (MP6)	32 × 32 × 256	2 × 2	/	/	/
21	Convolutional layer (C7)	32 × 32 × 256	3 × 3	/	Weights = 3 × 3 × 256 × 256 Bias = 1 × 1 × 256	256
22	ReLU (R7)	16 × 16 × 256	/	/	/	/
23	Maximum pooling layer (MP7)	16 × 16 × 256	2 × 2	/	/	/
24	Dropout_3	8 × 8 × 256	/	/	/	/
25	Flatten_1	2304	/	/	/	/
26	Dense_1	32	/	/	/	/
27	Dropout_4	32	/	/	/	/
28	Dense_2	1	/	/	/	/
29	ReLU (R8)	1	/	/	/	/

4.4 Methodology

Before starting our CNN architecture method, we must first carry out a simple image processing step. So, we start by compiling our image dataset. We need to look at our dataset. Right now, we're using the Jupiter notebook application. Before we start this project, we need to be quite familiar with Python. Our data images are loaded first. Even though this dataset contains more than 8,000 images, it takes some time to complete. The image labeling needs to be changed. It divided our image into the individual pixel intensities. This dataset's image has pixels that measure 224x224x3. Sometimes images are too big and need to be resized. In this case, we don't need to resize our data photographs. We then set up our dataset. The scale of the data is between 0 and 1, while its size spans from 0 to 224. As a result, the data can be classified using a number of different methods. Before training, the Image Data Generator Kera's function had one final modification. By just changing the existing data—using shifts, rotations, brightness changes, horizontal/vertical inversions, etc.—the goal is to expand the amount of training data. This function is only used after separating the data from training and testing. Our dataset was used to produce two datasets: a training dataset and a testing dataset. To prevent overfitting or bias, we utilize a training dataset that makes up 80% and a testing dataset that makes up 20%. The learning rate determines how quickly the neural network's weights change. The algorithm's epoch number indicates how many times the data is displayed, and each new period also updates the weight value. Every training cycle uses a certain amount of data, which is sample size. The weights updating algorithm is indicated by the optimizer value.

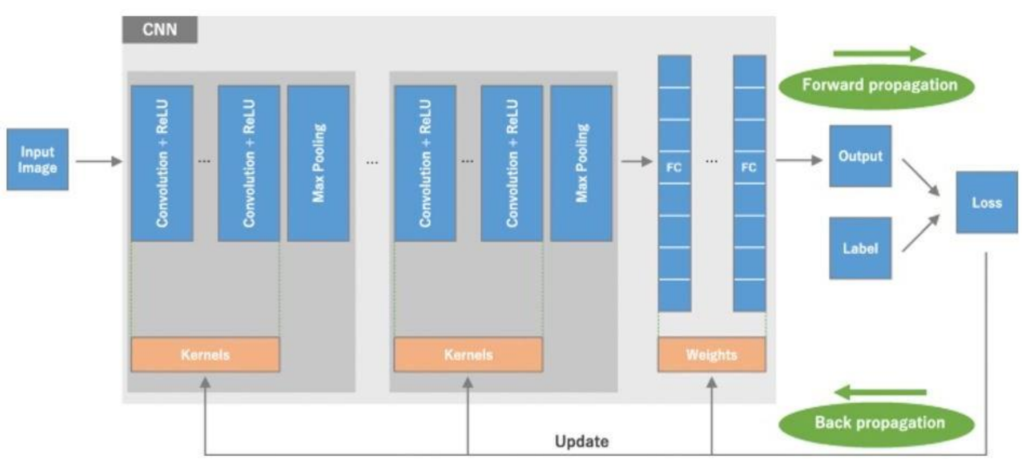


Figure 4.4: CNN Architecture

4.5 Training and Validation Accuracy

When training a machine learning model, overfitting is one of the most important things to avoid. This occurs when a model fits the training data well but is unable to generalize and generate correct predictions on new data.To determine if the model is overfitting, data scientists employ the cross-validation approach, in which they dividetheir data into the training set and the validation set. The training set is used to train the model, whereas the validation set is used

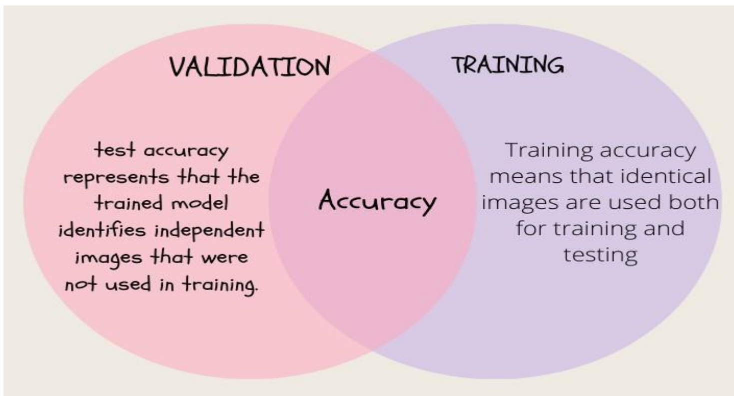


Fig 4.5: Type of Accuracy

exclusively to evaluate the performance of the model. On the validation set allow you to evaluate the quality of your model. Like how well it can generate predictions based on data. Consequently,train loss and train acc represent loss and accuracy on the training set, whereas value loss and value acc. represent lossand accuracy on the validation set. In Fig 4.6, we have shown Model training accuracy/loss curves. Parameters with a learning rate (initial) of INIT_LR = 1e-4, batch size BS = 32 and the number of epoch EPOCHS = 50. The graphs of loss nearly tendedto zero and the graphs of accuracy showed that after 30 training epochs, the model maintained a high accuracy 98.63% without overfitting.

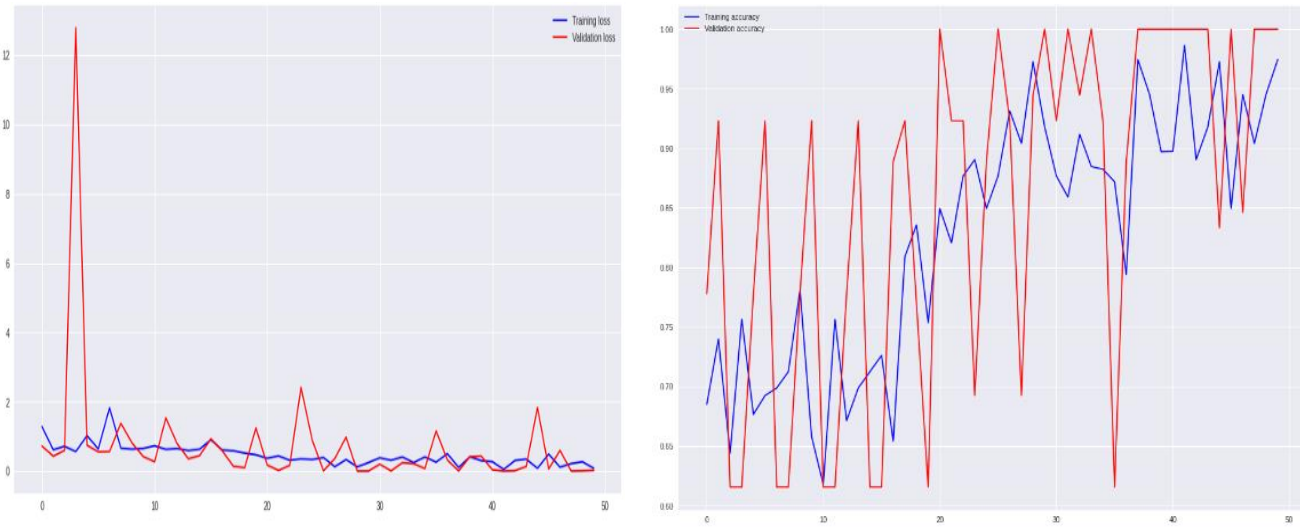


Fig 4.6: Training and Validation Accuracy-Loss graph & Training and Validation Accuracy graph

4.6 Classification Report

The performance of the models is measured using precision, recall, f1-score, and accuracy after completing thetraining and testing phase. The formulas that we used are as follows:

$$Accuracy = \frac{TP+TN}{P+N} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{FN+TP} \tag{3}$$

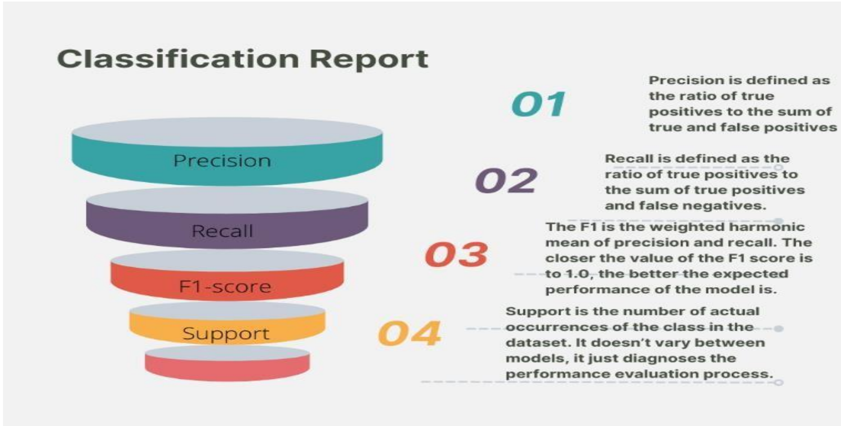


Fig 4.7 Classification report category

f1 Score = $\frac{2*(Precision* Recall)}{\text{Precision + Recall}}$

Where, TP= True Negative

TN= True Negative

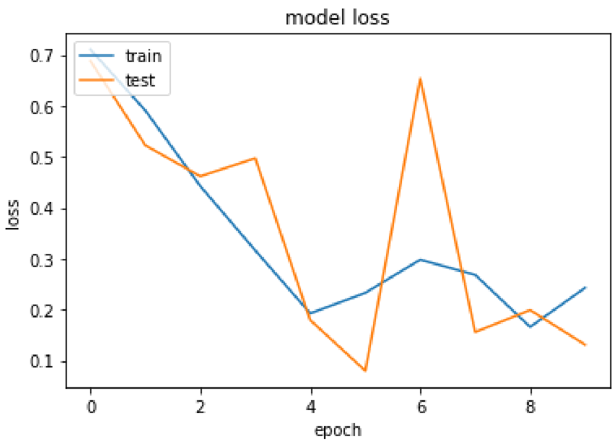
FP= False Positive

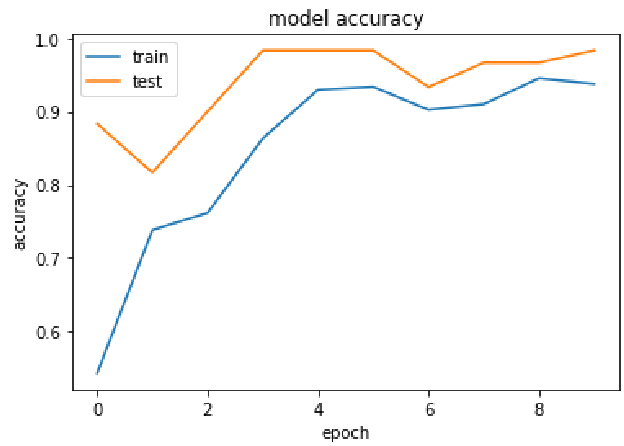
FN=False Negative

Class	n(truth)	n (classified)	Accuracy	Precision	Recall	F1 Score
1	153	144	95.49%	0.99	0.93	0.96
2	135	144	95.49%	0.92	0.99	0.95
Class	n (truth)	n (classified)	Accuracy	Precision	Recall	F1 Score
1	32	30	96.67%	1.0	0.94	0.97
2	28	30	96.67%	0.93	1.0	0.97

Table 4.2: Matric Result of CNN

We try to figure out the accuracy and loss together in a graph. For this we plot a graph of accuracy vs loss. The graph is given below





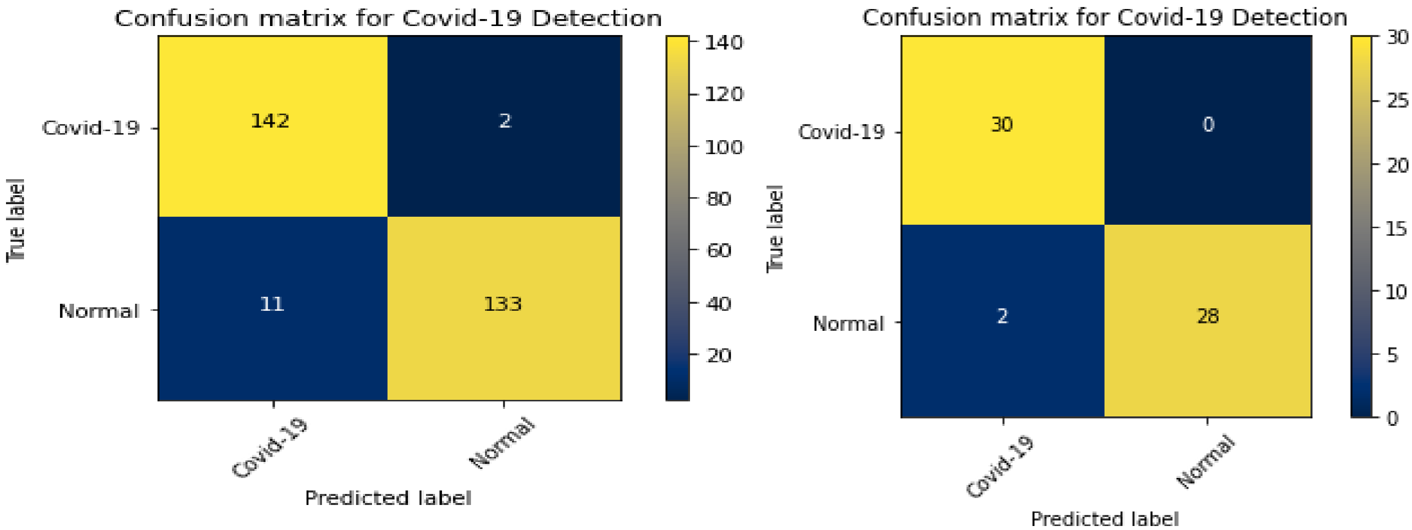
Summary of loss **Summary of Accuracy**

Fig 4.8: Loss & Accuracy graph

4.7 Confusion Matrix

A confusion matrix, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one (in unsupervised learning it is usually called a matching matrix). Each row of the matrix represents the instances in an actual class while each column represents the instances in a predicted class, or vice versa – both variants are found in the literature.

A validation dataset is a sample of data held back from training your model that is used to give an estimate of model skill while tuning model's hyper parameters. The validation dataset is different from the test dataset that is also held back from the training of the model, but is instead used to give an unbiased estimate of the skill of the final tuned model when comparing or selecting between final models. There is much confusion in applied machine learning about what a validation dataset is exactly and how it differs from a test dataset.



Confusion matrix of training dataset Confusion matrix & validation dataset

Fig. 4.9: Confusion matrix of training & Validation dataset

The confusion matrix is plotted with the help of heatmap showing a 2D matrix data in graphical format. It has successfully identified 142 true positives, 2 false negative in binary categorical. 11 false-positive, and 133 true negative value. In Sparse Categorical identified 30 true positives, 0 false negatives in binary categorical. 2 false-positive, and 28 true negative.

Chapter Five

5. Discussion & Conclusions

5.1 Conclusion

By including a COVID-19 X-ray imaging dataset, the proposed study uses a combined dataset of ray modality for chest illness identification. The data is enhanced with data to normalize in This preprocessed data eliminates any bias from the data. However, a unique CNN is suggested for

diagnosis of many chest diseases. It reports a validation accuracy of 87.89%, saturating learning

throughout training. Deep transfer learning is used to improve prediction outcomes and shorten

prediction times. In this manner, self-activated deep features of the proposed CNN's fully

connected layer are recovered. The ML method,

feeds the deep features to seven separate domain algorithms. Two methods of validation (5- and 10-fold) are used to make the suggested study more promising. By including a COVID-19 X-ray imaging dataset, the proposed study uses a combined dataset of X-ray modality for chest illness identification. The data is enhanced with data to normalize it. This preprocessed data eliminates any bias from the data. However, a unique CNN is suggested for the diagnosis of many chest diseases. It reports a validation accuracy of 87.89%, saturating learning throughout training. Deep transfer learning is used to improve prediction outcomes and shorten prediction times. In this manner, self-activated deep features of the proposed CNN's fully-connected layer are recovered. The ML method feeds the deep features to seven separate domain algorithms. Two methods of validation (5- and 10-fold) are used to make the suggested study more promising disease detection. It not only increases accuracy, but also reduces the prediction time of a given testing sample. Finally, a comparison shows the improvement of the proposed study from either single-class chest diseases or multi-class chest diseases, including COVID-19. In the future, multi-class decision-making CAD systems in different aspects of the medical domain should be used. However, data normalization needs to be considered to make the data reliable. Big data samples are encouraged for more confident results of chest diseases. The deep transfer of learning features is also encouraged.

5.2 Future Directions

This study proposes a two-stage deep residual learning method to detect pneumonia caused by COVID-19 using lung X-ray pictures. Using the machine learning model, the model per-formed well in identifying COVID-19 patients from those who had COVID-19-induced pneumonia. With an average sensitivity of 96.92 percent, specificity of 100 percent, andaccuracy of 98.63 percent, the model accurately predicted pneumonia. Accuracy is raisedwhile training loss is decreased. In the current situation, parallel testing can be utilized to stop the illness from spreading to front-line personnel and to produce first diagnosticsthat show whether a patient has COVID-19. As a result, the suggested technique can be utilized as a substitute diagnostic tool to identify pneumonia cases. By modifying the by-per parameters and transfer learning combinations, future research can enhance the CNNarchitecture's performance. An upgraded, complicated network structure might be an- other practical technique to choose the optimal model for pneumonia and COVID-19. We also want to develop our architecture one or two or three steps more. so that we can be able toensure a better Accuracy and precision in this architecture. The work is not all over. This is the primary level of work. We want to Go farther More with this Project.

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