Machine Learning Model To Detect Pneumonia Using Chest X-ray

Abstract:-

Pneumonia, a respiratory infection caused by the inflammation of air sacs due to viruses and bacteria, affects approximately 7% of the global population annually, with 4 million patients facing fatal risks. Early diagnosis is crucial, and typical symptoms include chest pain, shortness of breath, and cough. However, diagnosing pneumonia in children is challenging due to the low sensitivity of tests and weak clinical findings. Chest X-rays have become an important diagnostic tool, but the conventional approach involving manual examination by radiologists is time-consuming, subjective, and can vary in accuracy. To address this, the proposed model leverages machine learning (ML), specifically designed for image analysis, to automatically learn and extract relevant features from chest X-ray images. The dataset consists of annotated chest X-rays collected from diverse patient populations, including both pneumonia-positive and pneumonia-negative cases. This model holds significant implications for the medical field and patient care, as it can rapidly analyze large volumes of chest X-ray images and accurately detect pneumonia patterns with a high level of precision. This will enable healthcare professionals to prioritize urgent cases, expedite diagnosis, and promptly initiate appropriate treatments, leading to improved patient outcomes, reduced hospital stays, and optimized resource allocation within healthcare facilities.

CHAPTER-1

Introduction

1.1 Overview

Pneumonia is a form of acute respiratory infection that is most commonly caused by viruses or bacteria. It can cause mild to life-threatening illness in people of all ages, however it is the single largest infectious cause of death in children worldwide.

Pneumonia killed more than 808 000 children under the age of 5 in 2017, accounting for 15% of all deaths of children under 5 years. People at-risk for pneumonia also include adults over the age of 65 and people with preexisting health problems.

The lungs are made up of small sacs called alveoli, which fill with air when a healthy person breathes. When an individual has pneumonia, the alveoli are filled with pus and fluid, which makes breathing painful and limits oxygen intake. These infections are generally spread by direct contact with infected people.

Symptoms

1) Cough
2) Shortness of breath
3) Fever, sweating and shaking chills
4) Fatigue
5) Chest pain
6) Nausea, vomiting or diarrhea
7) Confusion, especially in older adults

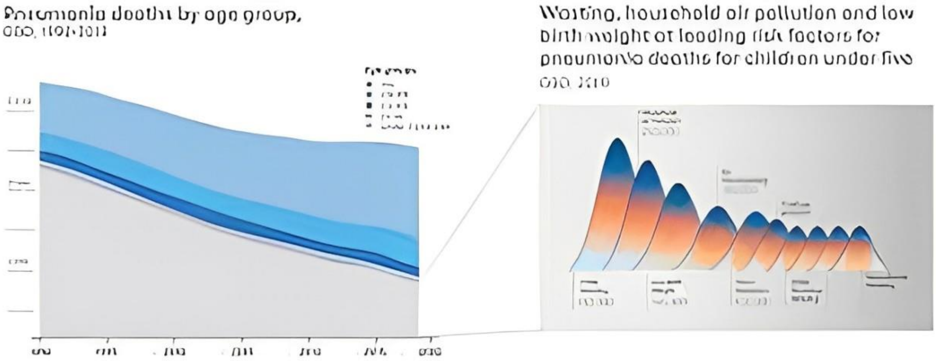

Fig 1.1. Death Rate

1.2 Research Motivation

Pneumonia is a serious respiratory infection that can lead to severe complications if not diagnosed and treated promptly. From past to present, infectious diseases are one of the most important factors that threaten human health. Pneumonia is one of the leading infectious diseases. It is the inflammation caused by the virus and bacteria that microscopically adversely affect the air sacs. Approximately 7% of the world's population is affected by pneumonia every year, and 4 million of the affected patients face fatal risks. So, early diagnosis is important in such diseases. Typical symptoms of pneumonia include chest pain, shortness of breath, cough, etc. are located. The diagnosis of pneumonia in childhood is difficult due to the low sensitivity of microbiological tests and weak clinical finding.

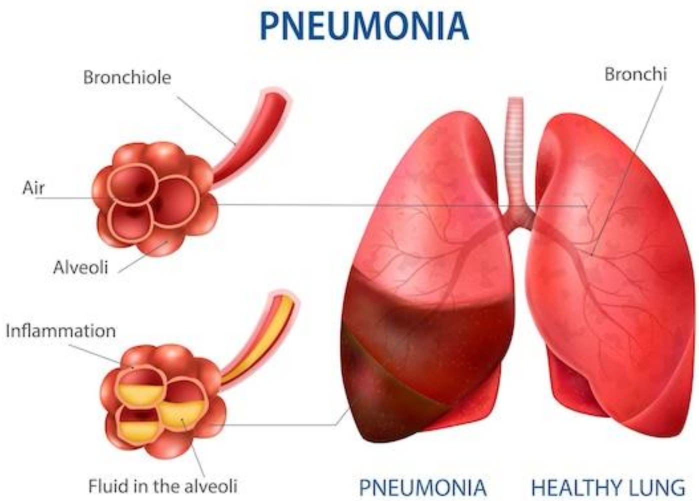

Fig 1.2. Infected Lung Image

Why We Need ?

Thus, the chest X-ray has become an important diagnostic tool in the diagnosis of pneumonia in children. The conventional approach to pneumonia detection from chest X-ray images involves manual examination by radiologists. These experts analyse X-ray images for specific patterns, such as opacities, infiltrates, or consolidation, to determine the presence of pneumonia. However, this process is time-consuming, subjective, and can vary in accuracy depending on the radiologist's experience. Consequently, there is a pressing need for an automated system that can provide consistent and reliable results. Due to this reasons, we proposed the advanced model based on present situations.

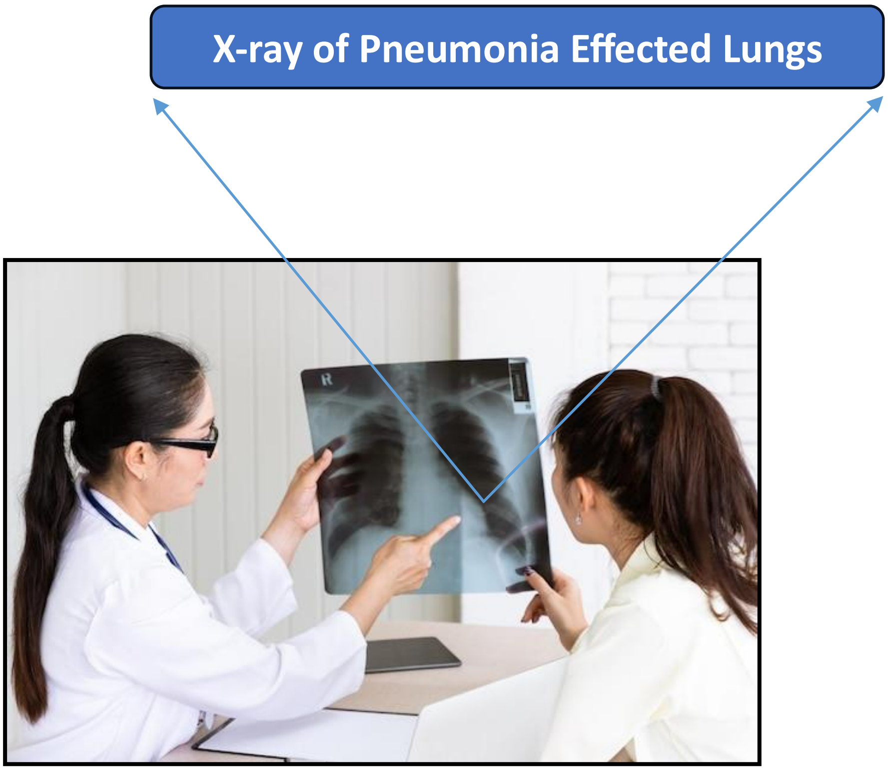

Fig 1.3. Chest X-Ray Image

How to Use ?

The proposed model leverages the power of ML, a supervised learning specifically designed for image analysis, to automatically learn and extract relevant features from the chest X-ray images. The dataset consists of many annotated chest X-rays collected from diverse patient populations, including both pneumonia-positive and pneumonia-negative cases. The proposed model holds significant implications for the medical field and patient care. This model can rapidly analyse large volumes of chest X-ray images and accurately detect pneumonia patterns with a high level of precision. This would enable healthcare professionals to prioritize urgent cases, expedite diagnosis, and promptly initiate appropriate treatments. Additionally, the model's ability to function as a valuable decision support tool can lead to improved patient outcomes, reduced hospital stays, and optimized resource allocation within healthcare facilities.

Fig 1.4. AI Lung Image

1.3 Traditional System

In the traditional healthcare system, the diagnosis of pneumonia is usually based on a combination of medical history, physical examination, and diagnostic tests Here is an overview of the process.

Medical History and Physical Exam:

During the medical history assessment, your healthcare provider may ask about your symptoms, when they started to occur, and any risk factors for pneumonia. They may query about exposure to sick individuals, recent travel, contact with animals, occupation, past and current medical conditions, medications, and smoking history. During the physical exam, your healthcare provider will check your temperature and listen to your lungs using a stethoscope. They will listen for unusual sounds such as crackling, gurgling, or rumbling, which may indicate pneumonia.

Diagnostic Procedures and Tests:

Based on your medical history and physical examination, your healthcare provider may recommend one or more diagnostic tests to rule out pneumonia and identify the infection's source. These examinations could consist of:
Chest X-ray: This imaging test looks for lung inflammation, which is commonly used to diagnose pneumonia.

Blood examinations: To evaluate the response of your immune system and look for indications of infection, a complete blood count (CBC) may be carried out.
Pulse oximetry: A tiny sensor that is affixed to your finger or ear is used in this non-invasive test to determine the amount of oxygen in your blood. It assists in assessing how well your lungs are able to oxygenate your blood.

Sputum test: To pinpoint the precise germ causing your pneumonia, a sample of your sputum (spit) or mucus may be taken.

Arterial blood gas test: This test uses a sample taken from an artery, usually in your wrist, to measure the oxygen levels in your blood if you are very sick.
Bronchoscopy: A bronchoscopy may be necessary in certain circumstances in order to view the airways and obtain lung tissue and fluid samples for additional examination.
Chest computed tomography (CT) scan: This imaging procedure can identify complications like lung abscesses or pleural disorders and gives more precise information about the degree of lung involvement.

Sputum test: A sample of your sputum (spit) or mucus may be taken in order to identify the specific germ causing your pneumonia.

Arterial blood gas test: If you are extremely ill, this test measures the amount of oxygen in your blood using a sample taken from an artery, usually in your wrist.
Bronchoscopy: In certain situations, a bronchoscopy may be required to view the airways and collect lung tissue and fluid samples for further analysis.
Chest computed tomography (CT) scan: This diagnostic technique provides more accurate information about the extent of lung involvement and can detect complications such as pleural disorders or lung abscesses.

1.4 Problem Statement

`Pneumonia detection using chest X-rays is a challenging task due to the subjective variability in the examination of chest X-rays. Chest X-ray imaging is the most frequently used method for diagnosing pneumonia, and it is a non-invasive and relatively inexpensive examination of the lungs. The classification of pneumonia can be done into four categories, including lobar pneumonia, bronchopneumonia, lobular pneumonia, and interstitial pneumonia.

The use of machine learning models, such as neural networks and MobileNet, has emerged as a powerful tool for detecting and diagnosing pneumonia from medical images such as chest X-rays. Computer-aided diagnostics improve the accuracy of diagnosis, and early diagnosis is the only feasible strategy for mitigating the disease's impact on the patients.

Fig 1.5.

1.5 Project Theme

AI-Driven Pneumonia Detection: Enhancing Traditional Diagnosis with Machine Learning.

Project Description: The project aims to develop a machine learning (ML) model for the early detection of pneumonia using chest X-ray images. By leveraging the power of artificial intelligence, this project seeks to enhance the traditional diagnostic methods used by healthcare providers.

Objective: The primary objective of this project is to create a robust ML model that can accurately classify chest X-ray images as either normal or indicative of pneumonia. By automating the detection process, the model aims to assist healthcare professionals in making faster and more accurate diagnoses, leading to improved patient outcomes.

Approach:

Data Collection and Preprocessing: Gather a large dataset of chest X-ray images from various sources, including both pneumonia-positive and pneumonia-negative cases. Preprocess the images to optimize their quality and remove any artifacts or noise that may impact the model's performance.

Model Development: Utilize deep learning techniques, such as convolutional neural networks (CNN), to train the ML model on the preprocessed chest X-ray images. The model will learn to extract relevant features and patterns from the images to differentiate between normal and pneumonia cases.

Model Validation and Performance Evaluation: Split the dataset into training and testing sets to evaluate the model's performance. Apply appropriate evaluation metrics, such as accuracy, precision, recall, and F1-score, to assess the model's ability to correctly classify pneumonia cases.

Comparison with Traditional Diagnosis: Compare the performance of the ML model with traditional diagnostic methods, such as physical examination and chest X-ray interpretation by healthcare providers. Analyze the model's strengths and limitations in terms of accuracy, speed, and potential for false positives or false negatives.

User Interface Development: Develop a user-friendly interface that allows healthcare providers to upload chest X-ray images and receive the model's prediction. The interface should provide clear and concise results, along with any necessary additional information or recommendations.

Deployment and Future Improvements: Deploy the ML model in a real-world healthcare setting, such as a hospital or clinic, to assess its practicality and usability. Collect feedback from healthcare professionals to identify areas for improvement and refine the model further based on their inputs.

The ultimate goal of this project is to harness the potential of machine learning to enhance the accuracy and efficiency of pneumonia diagnosis, ultimately improving patient care and outcomes. By integrating AI-driven technology with traditional diagnostic systems, this project opens new possibilities for the early detection and treatment of pneumonia, potentially saving lives and reducing healthcare costs.

1.6 Dataset Description

We have obtained a set of pneumonia chest x-rays (203), and we plan to utilize these images to train a machine learning model for pneumonia detection. The x-rays will serve as the primary data source for the development of the algorithm, allowing the machine learning system to learn and identify patterns associated with pneumonia in the images. By leveraging this dataset, we aim to enhance the accuracy and efficiency of pneumonia diagnosis through the application of machine learning technology. In order to train a machine learning model to detect normal chest X-rays, we can use existing chest X-ray data (203) that has been labelled as normal. According to a systematic review of machine learning applications for chest X-rays, there are many open sources of chest X-ray images available for research purposes. One study used a total of 203 normal chest X-ray images to train a machine learning model to classify normal and abnormal chest X-rays. Another study used a dataset of over 406 chest X-rays, including normal and pneumonia cases, to train a deep learning model for chest X-ray analysis. By using these existing datasets of normal chest X-rays, we can train a machine learning model to accurately detect normal cases and potentially improve the efficiency and accuracy of chest X-ray interpretation.

S.no	**Type of X-ray**	**Count**

1.	Pneumonia	203
2.	Normal	203

1.7 Advantages

Early Diagnosis: Chest X-ray imaging is widely used for pneumonia detection. An automated system can quickly identify potential cases, allowing for early intervention and treatment.

Scalability: Deep learning models can process large volumes of X-ray images efficiently, making them suitable for screening a large number of patients.

Consistency: Unlike human radiologists, AI models provide consistent results and do not suffer from fatigue or variability in interpretation.

Speed: Automated systems can analyze X-rays rapidly, reducing the time required for diagnosis.

Objective Assessment: AI models provide an objective assessment without being influenced by subjective factors.

1.8 Applications

1.8.1 Chest X-rays

To detect pneumonia from a chest X-ray, the following step-by-step process is typically followed:

1. Medical History and Physical Exam: The doctor will start by asking about the patient's medical history and performing a physical exam, including listening to the lungs with a stethoscope to check for abnormal sounds like crackling or wheezing.

2. Imaging Tests: If pneumonia is suspected, an imaging test may be performed to confirm the diagnosis. The primary imaging tests for pneumonia are chest X-ray (CXR) and computed tomography (CT) scan.

3. Interpretation of Chest X-ray: When interpreting the chest X-ray, the radiologist will look for white spots in the lungs (called infiltrates) that identify an infection.

4. Additional Tests: In some cases, additional tests such as blood tests, CT scan, pulse oximetry, and sputum test may be recommended to confirm the diagnosis and identify the type of organism causing the infection.

5. Treatment: Once pneumonia is diagnosed, the treatment involves curing the infection. Imagining findings help in determining the extent and location of the infection, which is crucial for management.

It's important to note that the interpretation of imaging tests should always be done in conjunction with the patient's clinical symptoms and other diagnostic findings[4]. Additionally, advancements in technology, such as the use of deep learning methods for the detection of pneumonia from chest X-ray images, are being explored to improve diagnostic accuracy.

Fig 1.6.

1.8.2 Blood Test

The complete process of pneumonia detection using a blood test involves several steps. When pneumonia is suspected, a doctor may recommend a complete blood count (CBC) to confirm an infection and identify the type of organism causing it. A CBC can show an elevated level of white blood cells, which is associated with some infections. Additionally, blood culture tests may be used to try to grow bacteria in a lab and identify the specific bacteria causing the infection. For patients with moderate or severe pneumonia who require hospitalization, 2 sets of blood cultures are usually obtained to assess for bacteremia and sepsis. Furthermore, other blood tests such as procalcitonin or C-reactive protein (CRP) may be conducted to help in the diagnosis. However, it's important to note that precise identification of the organism causing the infection isn't always possible with these tests.

In summary, the complete process of pneumonia detection using a blood test includes the following steps:

1. Complete Blood Count (CBC): To confirm the infection and identify the type of organism causing it.

2. Blood Culture Tests: To grow bacteria in a lab and identify the specific bacteria causing the infection.

3. Other Blood Tests: Such as procalcitonin or C-reactive protein (CRP) may be conducted to aid in the diagnosis.

These blood tests, along with other diagnostic procedures such as chest X-rays and physical examinations, play a crucial role in the accurate detection of pneumonia.

Fig 1.7.

1.8.3 CT Scan

To detect pneumonia from a CT scan, the following step-by-step process is typically followed:

1. Clinical Evaluation: The process usually begins with a clinical evaluation, including a medical history and physical examination, to assess the patient's symptoms and risk factors for pneumonia.

2. Chest X-ray: A chest X-ray is often the initial imaging test to diagnose pneumonia. It can help determine the extent and location of the infection, but it may not always provide a clear diagnosis of the type of pneumonia or its severity[3].

3. CT scan: If the chest X-ray results are inconclusive or if a more detailed image is needed, a chest CT scan may be recommended. CT scans are more sensitive than X-rays in detecting certain features of pneumonia, such as small nodules, ground-glass opacities, and bronchial wall thickening[2].

4. Interpretation: The CT scan images are interpreted by a radiologist, who assesses the presence, location, and extent of pneumonia. They may also consider the patient's symptoms and other clinical findings to make an accurate diagnosis[2].

5. Additional Tests: In some cases, additional tests such as blood tests, sputum culture, or pleural fluid analysis may be performed to identify the specific cause of pneumonia and guide treatment[3].

It's important to note that the use of CT scans for the initial evaluation of pneumonia is not always recommended, and their use should be based on clinical judgment and the specific needs of the patient[2].

The process of detecting pneumonia from a CT scan involves a combination of clinical evaluation, imaging tests, and the expertise of healthcare professionals to ensure an accurate diagnosis and appropriate treatment.

Fig 1.8.

1.9 Performance Metrics

Performance metrics are crucial for evaluating the effectiveness of AI fire detection systems. These metrics can include image complexity, accuracy, false positives, and false negatives. Image complexity metrics are based on the characteristics of fire detection and help assess the performance of the fire detection algorithm. Accuracy is a key metric that measures how well the system can distinguish between fire and non-fire images. False positives and false negatives are also important metrics to consider, as they can affect the reliability of the system.

1. **True Negatives (TN)**: These are instances where the system correctly identifies no fire when there is no fire present in the image or video feed.
2. **True Positives (TP)**: These are instances where the system correctly identifies a fire when a fire is present in the image or video feed.
3. **False Positives (FP)**: These occur when the system incorrectly identifies a fire when there is no fire present, leading to a false alarm.
4. **False Negatives (FN)**: These occur when the system fails to detect a fire that is actually present in the image or video feed.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision: Precision measures the proportion of true positive predictions (correctly identified weapons) out of all positive predictions made by the model. It helps in understanding the reliability of the model when it predicts that an image contains a weapon.

Precision = True Positives / (True Positives + False Positives)

Recall (Sensitivity): Recall measures the proportion of true positive predictions out of all actual positive instances in the dataset. It indicates the ability of the model to correctly detect weapons when they are present in the images.

Recall = True Positives / (True Positives + False Negatives)

F1 Score: The F1 score is the harmonic mean of precision and recall. It provides a single score that balances both precision and recall. F1 score is useful when there is an imbalance between the number of positive and negative instances in the dataset.

F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

Specificity: Specificity measures the proportion of true negative predictions (correctly identified non-weapons) out of all actual negative instances in the dataset. It is particularly relevant in scenarios where the consequences of false alarms (misclassifying non-weapons as weapons) are critical.

Specificity = True Negatives / (True Negatives + False Positives)

Chapter-2

2.1 Introduction

Pneumonia detection using machine learning models has revolutionized the medical field by offering efficient and accurate diagnostic capabilities. Pneumonia, an acute respiratory infection affecting the lungs, poses significant health risks, especially in regions with limited access to healthcare professionals. Pneumonia detection using ML has emerged as a informative technology in the field of medical safety. These systems leverage artificial intelligence to enhance early detection, reduce false assumptions, and provide valuable analytics for risk management. AI-based systems can detect diseases at an earlier stage than traditional detectors. AI algorithms can distinguish between real one and fake more effectively. Early diagnosis of pneumonia is critical for effective treatment and reducing mortality rates associated with the disease. Machine learning-assisted prediction models based on non-invasive measures like biomarkers and physical features have shown promising results in predicting pneumonia accurately In conclusion, the application of machine learning algorithms in pneumonia detection represents a significant advancement in medical diagnostics. These innovative approaches not only enhance diagnostic accuracy but also streamline the detection process, making it more accessible even in resource-constrained settings. The ongoing research focus on improving these models further underscores their potential to revolutionize pneumonia diagnosis and improve patient care outcomes.

2.2 Surveys

Ren et. al [1] studied two cases (a)investigated the performance disparities between geriatric and younger patients when using chest X-ray images to detect pneumonia, and (b)developed and tested a multimodal model called CheXMed that incorporated clinical notes together with image data to improve pneumonia detection performance for older people. Accuracy, precision, recall, and F1-score were used for model performance evaluation. CheXMed outperformed baseline models on all evaluation metrics. The accuracy, precision, recall, and F1-score were 0.746, 0.746, 0.740, 0.743 for CheXMed, 0.645, 0.680, 0.535, 0.599 for CheXNet, 0.623, 0.655, 0.521, 0.580 for DenseNet121, and 0.610, 0.617, 0.543, 0.577 for ResNet18.

Linghua et. al [2] proposed an anchor-free object detection framework and RSNA dataset based on pneumonia detection. First, a data enhancement scheme was used to preprocess the chest X-ray images; second, an anchor-free object detection framework was used for pneumonia detection, which contained a feature pyramid, two-branch detection head, and focal loss. The average precision of 51.5 obtained by Intersection over Union (IoU) calculation showed that the pneumonia detection results obtained in this study could surpass the existing classical object detection framework, providing an idea for future research and exploration.

Nalluri et. al [3] proposed AHGOA (Archimedes-assisted Henry Gas Optimization Algorithm) model selected the best characteristics from the retrieved features. It was the best option for avoiding the dimensionality curse. The selected EC + AHGOA method obtained good accuracy (~0.95) for tuning percentage 70 in pneumonia diagnosis from Chest X-ray images than some other previous techniques, including EC + AOA (~0.92), EC + HGSO (~0.93), EC + HGS (~0.88), EC + PRO (~0.90), and EC + BES (~0.89).

Mann’s et. al [4] proposed model, image preprocessing was performed using Student's t distribution, a compact probability density function (cPDF), for better sampling and segregation between the healthy and infected part of lungs, to improve the predictions. Further, a hybrid deep convolutional neural network model was built to extract image features by fine-tuning the pretrained models, viz. Resnet-50, EfficientNet, VGG-16, MobileNetV2 and DenseNet to achieve better results of diagnosis. The proposed hybrid model was analyzed using Grad-CAM visualization, which produced a course localization map, highlighting the infected region in the image used for prediction. The proposed hybrid model was evaluated based on governing parameters, viz. precision, recall, F1-score and accuracy. The results showed that the proposed model achieved a precision of 97.47%, recall of 98.09%, F1-score of 97.77%, and overall accuracy of 97.69% as compared to other existing models.

Udbhav et. al [5] proposed a project used ResNet, which performed well in image-recognition-related tasks and was an important part of a deep convolutional neural network. The project focused on proper classification, causes detection, and helped people avoid pneumonia infection by the use of (ANN) artificial neural networks and (CNN) convolutional neural network systems and their working methodologies. By the use of these techniques, many deaths could be stopped, helping people to live freely.

Lowie et. al [6] proposed the project, the data set contained 5,800 images, which was considerably less compared to deep-learning standards. In many situations, the count could even be hundreds or thousands, which was difficult to process on local machines. The model used in the project was quite heavy and would consume a lot of time to run on a normal CPU. To solve the issue, the project used Google Collaborator, which helped very much in learning the deep-learning model. Google Collab was a component of the Google Research project that supported machine-learning research and education and was hosted on a Google Cloud, which was available to everyone at no cost. By use of Collab, deep-learning needs could easily be fulfilled. For the image-based dataset, the project used ResNet, which performed well in image-recognition-related tasks and was an important part of a deep convolutional neural network. The project focused on proper classification, causes detection, and helped people avoid pneumonia infection by the use of (ANN) artificial neural networks and (CNN) convolutional neural network systems and their working methodologies. By the use of these techniques, many deaths could be stopped, helping people to live freely.

Omar et. al [7] studied, E. coli and K. pneumonia were isolated from infected urine samples, and the existence of the CTX-M resistant genes in ESBL-producing bacterial isolates of E. coli and K. pneumonia was determined. The antibacterial effect of Neem plant (A. indica) ethanolic extract against these bacteria was also determined. For phenotype detection of ESBLs, the hybrid disc method was used, and 12 available commercial antibiotics were used in the antibiotic susceptibility test. The tested bacterial isolates showed high resistance to these antibiotics. The PCR results confirmed that the ESBL-producing isolates E. coli and K. pneumonia had the CTX-M gene and the CTX-M-1 gene. The antibacterial activity of ethanolic extract of Neem plant against these bacteria was evaluated by the agar well diffusion method at different concentrations (50, 100, 200, and 300mg/ml). The inhibition zone diameters were (2, 4, 5, and 6mm) against E.coli (ESBL+) and (0, 2, 5, and 6mm) against K. pneumonia (ESBL+), respectively, while E.coli (ESBL-) was (7, 6, 4, and 3 mm) respectively, and with K. pneumonia (ESBL-) it gives (7, 6, 3, and 2 mm) respectively. The MIC for E.coli (ESBL+) was 125mg/ml, while the MIC for E.coli (ESBL-) was 62.5 mg/ml. The MIC for K. pneumonia (ESBL-) was at a concentration of 31.25mg/ml and for K. pneumonia (ESBL+) was at 62.5mg/ml. The ethanolic extract of Neem plant at different concentrations had antibacterial activity against (ESBL+) and (ESBL-) bacterial isolates of E. coli and K. pneumonia.

Chengxiang Zhang et. al [8] proposed a DBM-ViT model for deep learning. The model utilized CXR/CT lung images for effective health detection of normal, COVID-19, and other types of pneumonia. The model employed depthwise convolutions with different expansion rates to efficiently capture global information from CXR/CT lung images. Then, the lung feature maps with combined sequences were fed into the ViT module to capture local information. Multi-scale features combined with global and local information ensured maximum feature learning. The results showed that the detection accuracy of the DBM-ViT model in the CXR/CT image dataset reached 97.25%/98.36%. This method could effectively capture global and local information in lung images with high detection accuracy and could be used for rapid auxiliary diagnosis of pneumonia types.

Abdullayev Sardorbek et. al [9] was studied that the lung inflammation can be caused by exposure to airborne toxins or irritants, respiratory infections, and lung diseases like asthma or chronic bronchitis. Symptoms may include wheezing, shortness of breath, chest pain, and coughing. Lung inflammation can be acute (rapidly occurring and severe) or chronic (persistent or recurrent). Pneumonia is a lung infection that can make you feel sick. It happens when germs get into your lungs. Symptoms include coughing, fever, and difficulty breathing.

Ruopeng et. al [10] proposed the pneumonia model of C57BL/6 mice was established by intratracheal injection of LPS to evaluate the therapeutic effect of HHC on lung injury and inflammation in vivo. RAW264.7 macrophages were utilized to illustrate the cellular mechanism of HHC in vitro. HHC alleviated lung injury, ROS, and inflammatory cytokine IL-6 production in pneumonia mice in vivo. Molecular docking results disclosed the binding of HHC to JAK1 protein. The study further showed that HHC suppressed the inflammatory cytokines such as IL-6, TNF-α, IL-1β gene expression, inhibited the phosphorylation of JAK1 but not JAK3, and the subsequent STAT3 phosphorylation in LPS-activated macrophages. HHC exhibited no effects on the protein levels of JAK1 and STAT3 in vitro. Consistently, HHC also attenuated the JAK1, STAT3 phosphorylation in pneumonia mice in vivo. The results revealed that HHC attenuated pneumonia by targeted inhibition of the JAK1/STAT3 signaling pathway. It indicated the novel role of HHC to treat pneumonia, and its potential applications for JAK inhibitor-treated diseases.

Joelsons et. al [11] studied to identify the main microorganisms implicated in CAP by employing a multiplex Polymerase Chain Reaction (mPCR) at the foremost public hospital in Brazil. All patients who were admitted to the emergency department and diagnosed with severe CAP underwent an mPCR panel using nasopharyngeal and oropharyngeal swabs, with the aim of detecting 13 bacterial and 21 viral pathogens. A total of 169 patients were enrolled in the study. The mPCR panel identified an etiological agent in 61.5% of patients, with viruses being the most common (42.01%), led by Rhinovirus, followed by Influenza and Coronavirus (non-SARS-CoV-2). Bacterial agents were identified in 34.91% of patients, with S. pneumoniae being the most common, followed by H. influenzae, M. catarrhalis, and S. aureus. Additionally, the study found that the prescription for 92.3% of patients could be modified, with most changes involving de-escalation of antibiotics and antiviral therapy. The study revealed different etiological causes of CAP than those suggested by the Brazilian guidelines. Using molecular diagnostic tests, the researchers were able to optimize treatment by using fewer antibiotics.

Chaonan et. al [12] studied that included 156 children with severe CAP. Dynamic changes in platelet parameters, including platelet count (PLT), mean platelet volume (MPV), platelet distribution width (PDW) and plateletcrit (PCT), were recorded at 24 h, 48 h, 72 h, and day 7 of admission, as well as at discharge. At 72 h of admission, PLT in the viral infection group was significantly lower than that in the bacterial infection and bacterial and viral coinfections group. Meanwhile, the curve of changes in PLT (ΔPLT) in the viral infection group was clearly separated from the other two groups at this time point. Receiver operating characteristic (ROC) analysis showed that PLT at 72 h of admission could assist in distinguishing bacterial and viral infections in severe pneumonia children with the area under curve (AUC) value of 0.683 [95% confidence interval (CI): 0.561–0.805, P=0.007]. However, its sensitivity and specificity were not high, at 68% and 65%, respectively. Although the diagnostic value of platelet parameters in bacterial and viral infection in children with severe CAP is limited, they are still expected to be combined with other indicators to provide a reference for timely treatment.

Alfiansyah et.al [13] proposed the project which addressed in reducing pneumonia-related mortality by involving the development of an automatic screening system that analyzed X-ray images and distributed image data storage. This objective was achieved through a collaborative approach, employing Federated Learning to establish a platform that fostered cooperation of the hospitals. Each of them contributed to the advancement of diagnostics by constructing local models from their respective data. These local models were then transmitted to a central server that aggregated models to create a comprehensive global model. This process ensured that the resulting detection model remained unbiased. Importantly, patient data security was upheld, as the central server stored only global models but not sensitive patient information. The project also introduced an innovative system for archiving medical image data for a multifaceted purpose: it archived, anonymized, and secured images, while also curating a dataset necessary for training a Computer Assisted Diagnosis system. The work underlined the pushing of the boundaries of machine learning, especially in terms of the healthcare domain, with a strong emphasis on patient privacy and anonymity.

Falsey et.al [14] studied hospitalized adults with respiratory illness were recruited; sputa and clinical/laboratory data were collected. Sputa were cultured for bacteria and tested with BioFire PN. Microbial etiology was adjudicated by 4 physicians. Bacterial polymerase chain reaction (PCR) was compared with culture and clinical adjudication. The results showed that of 298 sputa tested, BioFire PN detected significantly more pathogens (350 bacteria, 16 atypicals, and 164 viruses) than sputum culture plus any standard-of-care testing (91% vs 60%, P < .0001). When compared with culture, the sensitivity of BioFire PN for individual bacteria was 46% to 100%; specificity, 61% to 100%; and negative predictive value, 92% to 100%. Cases were adjudicated as viral (n = 58) and bacterial (n = 100). PCR detected bacteria in 55% of viral cases and 95% of bacterial (P < .0001). High serum procalcitonin and bacterial adjudication were more often associated with sputa with 106 or 107 copies detected. Multiplex PCR testing of sputa for bacteria was useful to rule out bacterial infection with added value to detect viruses and atypical bacteria.

Chen et.al [15] studied patients with pneumonia were admitted to the Department of Pediatric Pulmonology of Xinhua Hospital between March-August 2019 and March-August 2020. And clinical characteristics of the patients in 2019 were compared with those in 2020. Hospitalizations for pneumonia decreased by 74% after the COVID-19 pandemic. For pathogens, virus, mycoplasma pneumoniae (MP) and mixed infection rates were all much lower in 2020 than those in 2019 ($P < 0.01$). Regarding allergens, compared with 2019, the positive rates of house dust mite, shrimp and crab were significantly higher in 2020 ($P < 0.01$). And for micronutrients, the levels of vitamin B2, B6, C and 25-hydroxyvitamin D (25(OH)D) in 2020 were observed to be significantly lower than those in 2019 ($P < 0.05$). For all the study participants, longer hospital stay ($OR = 1.521$, $P = 0.000$), milk allergy ($OR = 6.552$, $P = 0.033$) and calcium (Ca) insufficiency ($OR = 12.048$, $P = 0.019$) were identified as high-risk factors for severe pneumonia by multivariate analysis. The number of children hospitalized with pneumonia and incidence of common pathogen infections were both reduced, and that allergy and micronutrient status in children were also changed after the outbreak of the COVID-19 pandemic.

Zi-Yong et.al [16] investigated that Perillaldehyde decreased NLRP3 inflammasome activation and TNF-α expression in lung tissues by inhibiting the NF-κB pathway, and also impacted the MAPKs protein signalling pathway through the activation of TLR4. Notably, the use of high doses of Perillaldehyde for the treatment of pneumonia caused by A. baumannii 5F1 infection resulted in a survival rate of up to 80% in mice. In summary, it was demonstrated that Perillaldehyde is promising as a new drug for the treatment of pneumonia caused by A. baumannii 5F1 infection[1].

Ren et. al [17] They studied, investigated the performance disparities between geriatric and younger patients when using chest X-ray images to detect pneumonia, and developed and tested a multimodal model called CheXMed they incorporates clinical notes together with image data to improve pneumonia detection performance for older people. Accuracy, precision, recall, and F1-score were used for this model performance evaluation. CheXMed outperforms baseline models on all evaluation metrics. The accuracy, precision, recall, and F1-score are 0.746, 0.746, 0.740, 0.743 for CheXMed, 0.645, 0.680, 0.535, 0.599 for CheXNet, 0.623, 0.655, 0.521, 0.580 for DenseNet121, and 0.610, 0.617, 0.543, 0.577 for ResNet18.

Kaya et.al [18] They study aims to accurately detect pneumonia by proposing an ensemble CNN framework that incorporates optimal feature fusion. They were used novel image preprocessing algorithm has been developed that applies hierarchical template-matching to reduce image noise and improves the learning of relevant features. Instead of relying solely on a few pre-defined CNN models combined through majority voting, multiple CNN models with different architectures are trained on the pneumonia dataset using fine-tuning and transfer learning techniques. They obtain an optimal feature set, Chi-Square and mRMR methods iteratively eliminate irrelevant features from the fully connected layer of each CNN model. There optimal feature sets are then concatenated to enhance feature vector diversity for classification. There study's results illustrate that compared to state-of-the-art approaches, this framework achieves exceptional accuracy (98.94%) and F1 score (99.12%) on a public test dataset. These findings strongly support the conclusion that the proposed feature fusion-based model outperforms individual models and the majority voting ensemble method in terms of performance. The significance of this successful approach to pneumonia detection lies in its potential to provide clinicians and healthcare professionals with an effective solution for accurate and rapid diagnosis, particularly in pediatric cases.

Tran et.al [19] They prospective study was conducted among 467 children at the Thai Binh Paediatric Hospital, Vietnam between 1 July 2020 and 30 June 2021. Clinical data and laboratory results were collected. Twenty-four respiratory microorganisms were tested from nasopharyngeal swabs using real-time PCR. Logistical regression was used to estimate a factor's adjusted odd ratios of the severity of disease. Mean age of patients = 15.4 ± 13.3 months, 63.0% were male. Over 97% of patients had a positive PCR result. 87% of patients were positive for multiple (up to eight) microorganisms. Rhinovirus (46%), respiratory syncytial virus (RSV) (24%), enterovirus (17%), and parainfluenza viruses-3 (13%) were the most frequent viruses. H. influenzae (61%), S. pneumoniae (45%) and M. catarrhalis (30%) were the most common bacteria. 128 (27%) cases were classified as severe pneumonia. Presence of smokers at home (aOR 2.11, 95% CI 1.27–3.52, P value = 0.004), CRP level ≥ 50 mg/dL (aOR 6.11, 95% CI 3.86–9.68, P value < 0.0001), RSV (aOR 1.78, 95% CI 1.07–2.96, P value = 0.03) and H. influenzae (aOR 1.66, 95% CI 1.03–2.67, P value = 0.04) PCR detection associated with a higher risk of severe pneumonia; ,. Causative agents of pneumonia in children are complex. Children positive with RSV and H. influenzae need to be closely monitored to prevent severe pneumonia.

Jaiswal et.al [20] they describe deep learning based approach for the identification and localization of pneumonia in Chest X-rays (CXRs) images. Researchers usually employ CXRs for the diagnostic imaging study. Several factors such as positioning of the patient and depth of inspiration can change the appearance of the chest X-ray, complicating interpretation further. Our identification model (https://github.com/amitkumarj441/identify_pneumonia) is based on Mask-RCNN, a deep neural network which incorporates global and local features for pixel-wise segmentation. Our approach achieves robustness through critical modifications of the training process and a novel post-processing step which merges bounding boxes from multiple models. They were proposed identification model achieves better performances evaluated on chest radiograph dataset which depict potential pneumonia causes.

El Asnaoui, et.al [21] In this they present a comparison of recent deep convolutional neural network (CNN) architectures for automatic binary classification of pneumonia images based on fined tuned versions of (VGG16, VGG19, DenseNet201, Inception_ResNet_V2, Inception_V3, Resnet50, MobileNet_V2 and Xception) and a retraining of a baseline CNN. They proposed work has been tested using chest X-Ray & CT dataset, which contains 6087 images (4504 pneumonia and 1583 normal). As a result, they can conclude that the fine-tuned version of Resnet50 shows highly satisfactory performance with rate of increase in training and testing accuracy (more than 96% of accuracy).

Ansari et.al [22]In this proposes an effective, deep convolutional neural network with ResNet50 architecture for pneumonia detection.ResNet has performed quite well on the image recognition task and was a winner of the ImageNet challenge. A pre-trained ResNet-50 model is re-trained with the use of Transfer Learning on two different datasets of chest x-ray images. ResNet-50 based diagnostics model is found usefulfor pneumonia diagnostics despite significant variations in two datasets. They trained model has achieved an accuracy of 96.76%, which is at par with state-ofthe-art techniques available. RSNA dataset, with five times more images than the Chest X-ray Image dataset, took very little time for training. Also, because of theuse of the Transfer

Learning technique, both the models were able to learn the significant features of pneumonia with only 50% training dataset size. However the model can be improvised by using more deeper networks. Work can be extended to detect and classify both lung cancer and pneumonia using X-ray images

Praveen et. al [23] In this method ,they proposed detection of pneumonia infection by unsupervised fuzzy c-means classification learning algorithm is used. This approach gives better result than the rest of the methods. In fuzzy c-means, each resultant pixel gives accurate value since it has a weight associated with it.

Oliveira et.al [24] This method presented a novel approach based on computer-aided diagnostic (CAD) scheme and wavelet transforms to aid pneumonia diagnosis in children, using chest radiograph images. The prototype system, named Pneumo-CAD, was designed to classify images into presence (PP) or absence of pneumonia (PA).

Gopal et.al [25] provided the first preclinical evidence demonstrating that although diet-induced acute zinc deficiency (Zn-D: ~50% decrease) did not worsen infection induced by either influenza A (H1N1) or methicillin-resistant staph aureus (MRSA), Zn-D mice were sensitive to the injurious effects of superinfection of H1N1 with MRSA. Although the mechanism underlying the sensitivity of ZnD mice to combined H1N1/MRSA infection was unclear, it was noteworthy that this combination exacerbated lung injury as shown by lung epithelial injury markers (increased BAL protein) and decreased genes related to epithelial integrity in Zn-D mice (surfactant protein C and secretoglobins family 1A member 1). As bacterial pneumonia accounted for 25%–50% of morbidity and mortality from influenza A infection, zinc deficiency was suggested to be an important pathology component of respiratory tract infections.

Ding et.al [26] described a hospital-acquired pneumonia caused by K. ohmeri during veno-arterial extracorporeal membrane oxygenation. The fungal culture turned negative after the administration of caspofungin and amphotericin B. Extracorporeal membrane oxygenation (ECMO) was an adjunctive medical technique that provided temporary cardiopulmonary support for patients. Previous observations had suggested that the immune function of patients would typically decline during the use of ECMO, rendering infection to be one of the main complications of ECMO. K. ohmeri was a rare pathogenic fungus, particularly in immunocompromised individuals with vascular catheters, while amphotericin B was the most common antifungal therapy administered to treat K. ohmeri infections. It was important to raise awareness of rare fungal infections and actively treat them.

Ren et. al [27] They studied, investigated the performance disparities between geriatric and younger patients when using chest X-ray images to detect pneumonia, and developed and tested a multimodal model called CheXMed they incorporates clinical notes together with image data to improve pneumonia detection performance for older people. Accuracy, precision, recall, and F1-score were used for this model performance evaluation. CheXMed outperforms baseline models on all evaluation metrics. The accuracy, precision, recall, and F1-score are 0.746, 0.746, 0.740, 0.743 for CheXMed, 0.645, 0.680, 0.535, 0.599 for CheXNet, 0.623, 0.655, 0.521, 0.580 for DenseNet121, and 0.610, 0.617, 0.543, 0.577 for ResNet18.

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Parthasarathy et. al [29] The study presented a new Computer Aided Diagnosis using Harris Hawks Optimizer with Deep Learning (CAD-HHODL) method for Pneumonia Detection on CXR Images. The CAD-HHODL method investigated the CXR images for the recognition and classification of pneumonia. To obtain this, the CAD-HHODL method performed image pre-processing using a median filtering (MF) approach. For feature extraction, the residual network (ResNet50) model was used. Besides, the long short-term memory (LSTM) model could be utilized for the detection of pneumonia and its performance could be enriched by the use of the HHO model-based hyperparameter tuning process. The experimental results of the CAD-HHODL method were validated on the benchmark CXR database. The simulation values inferred the high performance of the CAD-HHODL method over other techniques.

Tran et.al [30] They prospective study was conducted among 467 children at the Thai Binh Paediatric Hospital, Vietnam between 1 July 2020 and 30 June 2021. Clinical data and laboratory results were collected. Twenty-four respiratory microorganisms were tested from nasopharyngeal swabs using real-time PCR. Logistical regression was used to estimate a factor's adjusted odd ratios of the severity of disease. Mean age of patients = 15.4 ± 13.3 months, 63.0% were male. Over 97% of patients had a positive PCR result. 87% of patients were positive for multiple (up to eight) microorganisms. Rhinovirus (46%), respiratory syncytial virus (RSV) (24%), enterovirus (17%), and parainfluenza viruses-3 (13%) were the most frequent viruses. H. influenzae (61%), S. pneumoniae (45%) and M. catarrhalis (30%) were the most common bacteria. 128 (27%) cases were classified as severe pneumonia. Presence of smokers at home (aOR 2.11, 95% CI 1.27–3.52, P value = 0.004), CRP level ≥ 50 mg/dL (aOR 6.11, 95% CI 3.86–9.68, P value < 0.0001), RSV (aOR 1.78, 95% CI 1.07–2.96, P value = 0.03) and H. influenzae (aOR 1.66, 95% CI 1.03–2.67, P value = 0.04) PCR detection associated with a higher risk of severe pneumonia; ,. Causative agents of pneumonia in children are complex. Children positive with RSV and H. influenzae need to be closely monitored to prevent severe pneumonia.

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Yao et al [33] they presented a method based on DeepConv-DilatedNet of identifying and localizing pneumonia in chest X-ray (CXR) images. Two-stage detector Faster R-CNN is adopted as the structure of a network. Feature Pyramid Network (FPN) is integrated into the residual neural network of a dilated bottleneck so that the deep features are expanded to preserve the deep feature and position information of the object. In this case of DeepConv-DilatedNet, the deconvolution network is used to restore high-level feature maps into its original size, and the target information is further retained. On the other hand, DeepConv-DilatedNet uses a popular fully convolution architecture with computation shared on the entire image. Then, Soft-NMS is used to screen boxes and ensure sample quality. Also, K-Means++ is used to generate anchor boxes to improve the localization accuracy. There developed algorithm obtained 39.23% Mean Average Precision (mAP) on the X-ray image dataset from the Radiological Society of North America (RSNA) and got 38.02% Mean Average Precision (mAP) on the ChestX-ray14 dataset, surpassing other detection algorithms. Algorithm that can provide doctors with location information of pneumonia lesions is proposed.

Ansari et.al [34]In this proposes an effective, deep convolutional neural network with ResNet50 architecture for pneumonia detection.ResNet has performed quite well on the image recognition task and was a winner of the ImageNet challenge. A pre-trained ResNet-50 model is re-trained with the use of Transfer Learning on two different datasets of chest x-ray images. ResNet-50 based diagnostics model is found usefulfor pneumonia diagnostics despite significant variations in two datasets. They trained model has achieved an accuracy of 96.76%, which is at par with state-ofthe-art techniques available. RSNA dataset, with five times more images than the Chest X-ray Image dataset, took very little time for training. Also, because of theuse of the Transfer Learning technique, both the models were able to learn the significant features of pneumonia with only 50% training dataset size. However the model can be improvised by using more deeper networks. Work can be extended to detect and classify both lung cancer and pneumonia using X-ray images.

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Sharma et.al [37] This systematic literature was reviewed meticulously discusses a wide range of techniques for detecting pneumonia using deep learning, including convolutional neural networks, pre-trained models, and ensemble models. The review provides an in-depth illustration of architecture and working process and evaluates the effectiveness of these models in solving various medical domain challenges. It presents a summarization and analytical discussion on convolutional neural networks-based, pre-trained, and ensemble models offering a deep insight into several factors, including performance measures, hyperparameters, and fine-tuning of the models. This meta-analysis also discusses the highly robust and outperforming ensemble pneumonia detection models. Furthermore, the review highlights various research gaps in the existing models, and probable solutions, enabling a deeper understanding of their performance and suitability for pneumonia detection tasks.

Goyal et.al [38] In this method, they proposed novel framework for the lung disease predictions like pneumonia and Covid-19 from the chest X-ray images of patients. The framework consists of dataset acquisition, image quality enhancement, adaptive and accurate region of interest (ROI) estimation, features extraction, and disease anticipation.

Sharma et.al [39] This research outcome exhibits that VGG16 with NN provides better performance than VGG16 with Support Vector Machine (SVM), VGG16 with K-Nearest Neighbour (KNN), VGG16 with Random Forest (RF), and VGG16 with Naïve Bayes (NB) for both datasets. Further, the proposed work results exhibit improved performance results for both datasets 1 and 2 in comparison to existing models.

Abubeker et.al [40] In this research aims to create a novel and efficient multiclass machine learning framework for analyzing and classifying chest x-ray images on a graphics processing unit (GPU). Researchers initially applied a geometric augmentation using a positional transformation function to the original dataset to enhance the sample size and aid future transfer learning. Models with the best accuracy, area under the receiver operating characteristics (AUROC), F1 score, precision, recall, and specificity are chosen from a pool of nine state-of-the-art neural network models. The best-performing models are then retrained using an ensemble technique using depth-wise convolutions, demonstrating significant improvements over the baseline models employed in this research. With a remarkable 97.69% accuracy, 100% recall, and 0.9977 AUROC scores, the proposed Bek-Bas network (B2-Net) model can differentiate between normal, bacterial, and viral pneumonia in chest x-ray images.

Yi et.al [41] The primary purpose of technology was developed algorithms and tools that assist humans and make their lives easier. This study proposed a scalable and interpretable deep convolutional neural network (DCNN) to identify pneumonia using chest X-ray images. The proposed modified DCNN model first extracts useful features from the images and then classifies them into normal and pneumonia classes. This proposed system has been trained and tested on chest X-ray images dataset .

Li et.al [42] This study aimed to develop a rapid, easily available, noninvasive machine learning diagnostic model for PCP among patients with severe pneumonia.

Khan et.al [43] In this method they propose the methodology of identifying the cause (either due to COVID-19 or other types of infections) of pneumonia from radiology images. Furthermore, because different variants of COVID-19 lead to different patterns of pneumonia, this proposed methodology identifies pneumonia, the COVID-19 caused pneumonia, and Omicron caused pneumonia from the radiology images.

Arun Prakash et.al [44] there work proposed Contrast Limited Adaptive Histogram Equalization for image enhancement and a stacking classifier based on the fusion of deep learning-based features for pediatric pneumonia diagnosis. There extracted features from the global average pooling layers of the fine-tuned MobileNet, DenseNet121, DenseNet169, and DenseNet201 are concatenated for the final classification using a stacked ensemble classifier.

Sharma et .al [45] this deep learning-based model called VGG19 is used to address this issue, which classifies pneumonia from normal lungs. A chest X-ray dataset containing 5856 images was used in this study to classify pneumonia from normal lungs. The outcomes have been demonstrated as accuracy, precision, recall, F1-score, and receiver operating characteristics with the values of 93%, 0.931, 0.93, 0.931, and 0.973.

Madhuri et.al [46] In this project Hybrid Convolution Neural Network (CNN) is used with Machine Learning Classifiers to detect Pneumonia disease from the Chest X-rays, which are used in the real world by medical professionals to find pneumonia. Computer-Aided Diagnosis (CAD) systems may be improved with the application of deep learning and machine learning based technologies, which can be of assistance to radiologists and doctors when making medical decisions.

Jyothi et.al [47] A hybrid Convolutional Neural Network (CNN) model was proposed based on Machine Learning (ML) classifiers. This mechanism detects if a person has pneumonia or not. This mechanism was attached to a user interface where people can use and know whether they have pneumonia or not.

Pintelas et.al [48] they proposed novel explainable feature extraction and prediction framework applied to 3D image recognition. In particular, they proposed a new set of explainable features based on mathematical and geometric concepts, such as lines, vertices, contours, and the area size of objects. These features are calculated based on the extracted contours of every 3D input image slice. In order to validate the efficiency of the proposed approach, they applied it to a critical real-world application: pneumonia detection based on CT 3D images.

Malik et.al [49] A multi-classification method based on the deep learning (DL) model was developed and tested in this work to automatically classify the COVID-19, LC, pneumothorax, TB, and pneumonia from chest x-ray images. COVID-19 and other chest tract disorders are diagnosed using a convolutional neural network (CNN) model called CDC Net that incorporates residual network thoughts and dilated convolution.

Xue et.al [50] This research explore the different DL techniques for identifying COVID-19 and pneumonia on medical CT and radiography images using ResNet152, VGG16, ResNet50, and DenseNet121. ResNet framework uses CT scan images with accuracy and precision. This research automates optimum model architecture and training parameters. Transfer learning approaches are also employed to solve content gaps and shorten training duration.

Miah et.al [51] they proposed deep-learning methods for predicting COVID-19 detection using chest X-ray images. Chest X-ray imaging has become an essential diagnostic tool in the management of COVID-19, as it is non-invasive, widely available, and cost-effective However, the interpretation of chest X-rays for COVID-19 detection can be challenging, as the radiographic features of COVID-19 pneumonia can be subtle and overlap with other respiratory diseases.

Sardar et.al 52] . In this method, an attempt has been made to differentiate COVID-19 CT scan images from that of non COVID-19 using AI/ML. A detailed study has been done on the artificial neural networks used worldwide by various researchers for this classification. Convolution Neural Network (CNN) being the most effective classifier for images, has been used in this study to build a neural network (Covi-net) that can classify COVID-19 and nonCOVID-19 images with 97.6% accuracy.

Kandati et.al [53] in this unified framework combining FL and a particle swarm optimization algorithm (PSO) to speed up the government's response time to chest lesion caused by COVID-19 infection outbreaks. The Federated Particle Swarm Optimization approach is tested on a multidimensional chest lesion caused by the COVID-19 infection image dataset and the chest X-ray (pneumonia) dataset from Kaggle's repository. Our research shows that the proposed model works better when there is an uneven amount of data, has lower communication costs, and is therefore more efficient from a network's point of view.

Nahiduzzaman et.al [54] In this method an intelligent recognition system for seven lung diseases has been proposed based on machine learning (ML) techniques to aid the medical experts. Chest X-ray (CXR) images of lung diseases were collected from several publicly available databases. A lightweight convolutional neural network (CNN) has been used to extract characteristic features from the raw pixel values of the CXR images. The best feature subset has been identified using the Pearson Correlation

Coefficient (PCC). Finally, the extreme learning machine (ELM) has been used to perform the classification task to assist faster learning and reduced computational complexity. The proposed CNN-PCC-ELM model achieved an accuracy of 96.22% with an Area Under Curve (AUC) of 99.48% for eight class classification.

Garg et. al [55] The main objective of this study is to determine whether a patient has pneumonia using a chest X-ray picture. CNN is used for this for this process, as it's great processing capability makes them the most effective choice for image processing and categorization. By the use of CNN, results will be obtained rapidly, and dependence on medical personnel will be reduced. Additionally, it will produce more precise findings than human vision, which could overlook a little X-Ray feature.

Sarp et. al [56] .this proposed model leverages transfer learning and data augmentation techniques for faster and more adequate model training. Lung segmentation is applied to enhance the model performance further. they conducted a pre-trained network comparison with the highest classification performance (F1-Score: 98%) using the ResNet model.

Dey et. al [57] This research to develop a Deep-Learning System (DLS) to diagnose the lung abnormality using chest X-ray (radiograph) images. In this work is implemented using; (i) Conventional chest radiographs and (ii) Chest radiograph treated with a threshold filter. The initial experimental evaluation is carried out using the traditional DLS, such as AlexNet, VGG16, VGG19 and ResNet50 with a SoftMax classifier. This results confirmed that, VGG19 provides better classification accuracy (86.97%) compared to other methods. Later, a customized VGG19 network is proposed using the Ensemble Feature Scheme (EFS), which combines the handcrafted features attained with CWT, DWT and GLCM with the Deep-Features (DF) achieved using Transfer-Learning (TL) practice.

Goyal et. al [58] they formulated a robust technique to enhance the detection and classification results. Soft computing methods such as artificial neural network (ANN), support vector machine (SVM), K-nearest neighbour (KNN), ensemble classifier, and deep learning classifier are used for classification. To accurate detection of lung disease, deep learning architecture has been proposed using recurrent neural network (RNN) with long short-term memory (LSTM).

Ibrahim et.al [59] they proposed model achieved 94.43% accuracy, 98.19% sensitivity, and 95.78% specificity. For bacterial pneumonia and normal CXR images, the model achieved 91.43% accuracy, 91.94% sensitivity, and 100% specificity. For COVID-19 pneumonia and normal CXR images, this model achieved 99.16% accuracy, 97.44% sensitivity, and 100% specificity. For this classification CXR images of COVID-19 pneumonia and non-COVID-19 viral pneumonia, the model achieved 99.62% accuracy, 90.63% sensitivity, and 99.89% specificity.

Khan et. al [60] automated systems have been proposed for the rapid detection of pneumonia from chest X-rays. Although several algorithms are currently available for pneumonia detection, a detailed review summarizing the literature and offering guidelines for medical practitioners is lacking.

Nahid et.al [61] they have been trying to develop a method to automatically detect Pneumonia using machines by analyzing and the symptoms of the disease and chest radiographic images of the patients for the past two decades. However, with the development of cogent Deep Learning algorithms, the formation of such an automatic system is very much within the realms of possibility. In this paper, a novel diagnostic method has been proposed while using Image Processing and Deep Learning techniques that are based on chest X-ray images to detect Pneumonia.

2.3 Research Gap:-

Sno	Author	Title	Advantage	Drawback	Accuracy
1	Ren	CHEX MED: A MULTIMODAL LEARNING ALGORITHM FOR PNEUMONIA DETECTION IN THE ELDERLY	They can improve pneumonia detection accuracy, which is especially useful for the elderly in parts of the world where access to experienced	medical records data are crucial behavioural factors such as excessive alcohol consumption, in addition to socio-economic variables and genetic predispositions	74.6%

			radiologists is limited		
2	Linghua Wu	PNEUMONIA DETECTION BASED ON RSNA DATASET AND ANCHOR-FREE DEEP LEARNING DETECTOR	the advantage of being simpler than previous first-order detectors based on anchor frames	By removing the pre-defined anchor boxes, FCOS completely avoids the complex operations on anchor boxes, such as calculating the overlap during training, and saves the memory usage during training.	**85%**
3	Naseem Ansari	EFFECTIVE PNEUMONIA DETECTION USING RESNET BASED TRANSFER LEARNING	ResNet-50 based diagnostics model is found useful for pneumonia diagnostics despite significant variations in two datasets	By changing the data set training ratio they rest of got less accuracy	96.76%
4	Shangjie Yao	PNEUMONIA DETECTION USING AN IMPROVED ALGORITHM BASED ON FASTER R-CNN	, K-Means++ is used to generate anchor boxes to improve the localization accuracy	The latter uses an additional stage to complete the task of multiscale target detection. They are faster than two-stage detectors but less accurate	98%
5	Arfat Ahmad Khan	DETECTION OF OMICRON CAUSED PNEUMONIA FROM	unveil that the proposed step-by-step solution enhances the accuracy of	By changing the data set training ratio they rest of got less accuracy	93%

		RADIOLOGY IMAGES USING CONVOLUTION NEURAL NETWORK (CNN)	pneumonia detection along with finding its cause, despite having a limited dataset.		
6	K M Abubeker	B2-NET: AN ARTIFICIAL INTELLIGENCE POWERED MACHINE LEARNING FRAMEWORK FOR THE CLASSIFICATION OF PNEUMONIA IN CHEST X-RAY IMAGES	This research aims to create a novel and efficient multiclass machine learning framework for analyzing and classifying chest x-ray images on a graphics processing unit (GPU)	The B2-Net framework uses an 80:10:10 distribution for training, testing, and validation datasets. This fixed distribution may not be suitable for all types of datasets and could potentially limit the framework's performance in certain scenarios	97.69%
7	Rong Yi	DENTIFICATION AND CLASSIFICATION OF PNEUMONIA DISEASE USING A DEEP LEARNING-BASED INTELLIGENT COMPUTATIO	The proposed system has been trained and tested on chest X-ray images dataset. Various performance metrics have been utilized to inspect the stability and efficacy of the proposed model. The experimental	By changing the data set training ratio they rest of got less accuracy	96.09%

		NAL FRAMEWORK	result shows that the proposed model's performance is greater compared to the other state-of-the-art methodologies used to identify pneumonia.		
8	Arfat Ahmad Khan	DETECTION OF OMICRON CAUSED PNEUMONIA FROM RADIOLOGY IMAGES USING CONVOLUTION NEURAL NETWORK (CNN)	unveil that the proposed step-by-step solution enhances the accuracy of pneumonia detection along with finding its cause, despite having a limited dataset.	CNNs are primarily designed to capture local patterns and features in data. They may struggle to capture long-term dependencies or relationships that span across larger contexts. Recurrent Neural Networks (RNNs) are often used in conjunction with CNNs	87%
9	J Arun Prakash	PEDIATRIC PNEUMONIA DIAGNOSIS USING STACKED ENSEMBLE LEARNING ON MULTI-MODEL DEEP	contrast Limited Adaptive Histogram Equalization for image enhancement and a stacking classifier based on the fusion of deep	CNNs can be computationally intensive and require significant computational resources, especially for training large models on large datasets. This	99%

		CNN ARCHITECTURES	learning-based features for pediatric pneumonia diagnosis.	hardware dependence can limit the scalability and accessibility of CNNs.	
10	Xingsi Xue	DESIGN AND ANALYSIS OF A DEEP LEARNING ENSEMBLE FRAMEWORK MODEL FOR THE DETECTION OF COVID-19 AND PNEUMONIA USING LARGE-SCALE CT SCAN AND X-RAY IMAGE DATASETS	This research automates optimum model architecture and training parameters. Transfer learning approaches are also employed to solve content gaps and shorten training duration. An upgraded VGG16 deep transfer learning architecture is applied to perform multi-class classification for X-ray imaging tasks.	Deep learning ensemble frameworks can be computationally intensive and require significant computational resources, especially for training large models on large datasets. This computational complexity can limit the scalability and accessibility of deep learning ensemble frameworks.	95%
11	Leandro Luıs Galdino Oliveira	COMPUTER-AIDED DIAGNOSIS IN CHEST RADIOGRAPHY FOR DETECTION OF	The performance of the Pneumo-CAD was evaluated by a subset of images randomly selected from the	Pneumo-CAD could represent a complementary tool to screen children with clinical suspicion of pneumonia, and so to contribute to gather	90%

		CHILDHOOD PNEUMONIA	knowledge database. The retrieval of similar images was made by feature extraction using wavelets transform coefficients of the image.	information on the burden of- pneumonia estimates in order to help guide health policies toward preventive interventions	
12	Naveed Ahmad	EFFECTIVE DETECTION OF LUNG DISEASE FROM X-RAY IMAGES USING CONVOLUTIONAL NEURAL NETWORKS (CNNS) AND VARIOUS ARCHITECTURES	In this study, we used InceptionResNet V2, DenseNet121, VGG16, and Xception, Convolutional neural networks (CNNs) in four distinct configurations. To make a model work better, we need a large dataset.	CNNs are not inherently invariant to changes in the position or orientation of objects within an image. This means that if an object is shifted or rotated within an image, the CNN may struggle to correctly classify it	98.33%
13	Niloy Sikder	A NOVEL METHOD TO IDENTIFY PNEUMONIA THROUGH ANALYZING CHEST RADIOGRAPH	the Convolutional Neural Network (CNN) based algorithm on a chest X-ray dataset to classify pneumonia. The objective and	While CNNs are highly effective for many image recognition tasks, their performance may be limited in certain scenarios. For example, CNNs may	95%

		S EMPLOYING A MULTICHANNEL CONVOLUTIONAL NEURAL NETWORK	automated detection of pneumonia represents a serious challenge in medical imaging because the signs of the illness are not	struggle with small datasets, as they require a large amount of data to achieve high accuracy rates. Additionally, CNNs may have high computational requirements, which can limit their practicality in resource-constrained environments.	
14	Sravani Nalluri	Pneumonia screening on chest X-rays with optimized ensemble model	The gathered image is initially pre-processed using Dynamic Histogram Equalization (DHE), followed in this case by median filtering. At the segmentation phase, by utilizing the Enhanced Watershed Segmentation, the ROI is separated from the background region of the pre-processed image	If the individual models in the ensemble are trained independently or sequentially without considering their interactions, there may be a lack of diversity in the ensemble. This lack of diversity can limit the ensemble's ability to generalize beyond the training data.	75%

15	Khan	A COMPARATIVE STUDY OF DETECTING COVID 19 BY USING CHEST X-RAY IMAGES– A DEEP LEARNING APPROACH	The use of deep learning algorithms in radiological imaging could significantly enhance the accuracy of diagnosis for this virus.	nsemble learning methods, including deep learning ensemble frameworks, aim to improve the performance of individual models by combining them. However, the success of ensemble methods depends on various factors, such as the training of baseline models and the fusion method used.	90%

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Chapter 3

3.1 Naive Bayes

Naive Bayes classifiers are a collection of classification algorithms based on Bayes' Theorem. It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e. every pair of features being classified is independent of each other. To start with, let us consider a dataset.

One of the most simple and effective classification algorithms, the Naïve Bayes classifier aids in the rapid development of machine learning models with rapid prediction capabilities.

Why is it called Naive Bayes?

The "Naive" part of the name indicates the simplifying assumption made by the Naïve Bayes classifier. The classifier assumes that the features used to describe an observation are conditionally independent, given the class label. The "Bayes" part of the name refers to Reverend Thomas Bayes, an 18th-century statistician and theologian who formulated Bayes' theorem.

Advantages of Naive Bayes Classifier

- Easy to implement and computationally efficient.
- Effective in cases with a large number of features.

- Performs well even with limited training data.

Disadvantages of Naive Bayes Classifier

- Assumes that features are independent, which may not always hold in real-world data.
- Can be influenced by irrelevant attributes.
- May assign zero probability to unseen events, leading to poor generalization.

Chapter 4

4.1 Overview

A respiratory infection called pneumonia has the potential to be fatal if it is not identified and treated quickly. Through the analysis of medical images, such as chest X-rays, machine learning (ML) algorithms can help detect pneumonia by finding patterns that are suggestive of the illness. The main goal of this project is to detect pneumonia using the Random Forest (RF) algorithm.

Dataset:
The RF model will be trained and evaluated using a dataset of chest X-ray pictures. Chest X-Ray Images (CXR) is a frequently used dataset that includes many chest X-ray images with the labels "Normal" or "Pneumonia."

Firstly, we gathered relevant medical data, including patient histories, physical examination results, and diagnostic tests, such as chest X-rays and blood tests. This data served as the foundation for training our machine learning model.

Next, we preprocessed the collected data by cleaning and organizing it to ensure its quality and compatibility with the machine learning algorithm. This step involved handling missing values, normalizing features, and encoding categorical variables, among other preprocessing techniques.

We then proceeded to train our Random Forest model using the preprocessed data. This algorithm is well-suited for classification tasks and has shown promising results in medical diagnosis. During the training phase, the model learned to distinguish between pneumonia and non-pneumonia cases based on the provided features.

After training, we evaluated the performance of our model using various metrics, such as accuracy, precision, recall, and F1-score. This evaluation helped us assess the effectiveness of our system in accurately detecting pneumonia cases.

To further enhance the accuracy and generalization capability of our model, we performed hyperparameter tuning, optimizing the parameters of the Random Forest algorithm. By finding the best combination of parameters, we aimed to improve the model's performance and reduce the risk of overfitting.

Once satisfied with the model's performance, we deployed it in a user-friendly interface or integrated it into a larger healthcare system. This allowed healthcare providers to input patient data and receive real-time predictions on the likelihood of pneumonia.

Throughout the project, we prioritized the interpretability and explainability of our model. This involved analyzing the significance of the features used in the prediction process, allowing healthcare professionals to understand the factors contributing to the pneumonia diagnosis.

Overall, our project successfully developed a pneumonia detection system using the Random Forest algorithm. By leveraging machine learning techniques, we aimed to assist healthcare providers in making accurate and timely diagnoses, ultimately improving patient outcomes and optimizing healthcare resources.

4.2 Parameters

4.2.1 Flattern

Flattening is a technique that is used to convert multi-dimensional arrays into a 1-D array, it is generally used in Deep Learning while feeding the 1-D array information to the classification mode Multi-Dimensional arrays take more amount of memory while 1-D arrays take less memory, which is the most important reason why we flatten the **Image Array** before processing/feeding the information to our model. In most cases, we will be dealing with a dataset which contains a large amount of images thus flattening helps in decreasing the memory as well as reducing the time to train the model.

4.3 Data Splitting

Splitting facts for system mastering models is an crucial step within the version improvement process. It includes dividing the to be had dataset into separate subsets for education, validation, and trying out the version. Here are a few common processes for splitting data:

1. Train-Test Split: The dataset is divided right into a training set and a trying out set. The education set is used to educate the model, even as the checking out set is used to assess the model's overall performance. The regular cut up is 70-eighty% for training and 20-30% for checking out, but this may vary depending on the scale of the dataset and the precise use case.
2. Train-Validation-Test Split: The dataset is split into three subsets – a schooling set, a validation set, and a trying out set. The training set is used to train the version, the validation set is used to tune hyperparameters and validate the version's overall performance for the duration of training, and the testing set is used to evaluate the very last version's overall performance.

4.4 Random Forest Classifier

A random forest is an ensemble learning method that combines the predictions from multiple decision trees to produce a more accurate and stable prediction. It is a type of supervised learning algorithm that can be used for both classification and regression tasks.

Every decision tree has high variance, but when we combine all of them in parallel then the resultant variance is low as each decision tree gets perfectly trained on that particular sample data, and hence the output doesn't depend on one decision tree but on multiple decision trees. In the case of a classification problem, the final output is taken by using the majority voting classifier. In the case of a regression problem, the final output is the mean of all the outputs. This part is called **Aggregation**.

What is Random Forest Regression?

Random Forest Regression in machine learning is an ensemble technique capable of performing both regression and classification tasks with the use of multiple decision trees and a technique called Bootstrap and Aggregation, commonly known as bagging. The basic idea behind this is to combine multiple decision trees in determining the final output rather than relying on individual decision trees.

Random Forest has multiple decision trees as base learning models. We randomly perform row sampling and feature sampling from the dataset forming sample datasets for every model. This part is called Bootstrap.

We need to approach the Random Forest regression technique like any other machine learning technique.

Advantages of Random Forest Regression :

- It is easy to use and less sensitive to the training data compared to the decision tree.
- It is more accurate than the decision tree algorithm.
- It is effective in handling large datasets that have many attributes.
- It can handle missing data, outliers, and noisy features.

Disadvantages of Random Forest Regression :

- The model can also be difficult to interpret.
- This algorithm may require some domain expertise to choose the appropriate parameters like the number of decision trees, the maximum depth of each tree, and the number of features to consider at each split.
- It is computationally expensive, especially for large datasets.
- It may suffer from overfitting if the model is too complex or the number of decision trees is too high

Real applications include:

- Medical Diagnosis: Identifying diseases based on patient data.
- Finance: Credit scoring for risk assessment in lending.

CHAPTER 5

MACHINE LEARNING

What is Machine Learning

Before we take a look at the details of various machine learning methods, let's start by looking at what machine learning is, and what it isn't. Machine learning is often categorized as a subfield of artificial intelligence, but I find that categorization can often be misleading at first brush. The study of machine learning certainly arose from research in this context, but in the data science application of machine learning methods, it's more helpful to think of machine learning as a means of building models of data.

Fundamentally, machine learning involves building mathematical models to help understand data. "Learning" enters the fray when we give these models tunable parameters that can be adapted to observed data; in this way the program can be considered to be "learning" from the data. Once these models have been fit to previously seen data, they can be used to predict and understand aspects of newly observed data. I'll leave to the reader the more philosophical digression regarding the extent to which this type of mathematical, model-based "learning" is similar to the "learning" exhibited by the human brain. Understanding the problem setting in machine learning is essential to using these tools effectively, and so we will start with some broad categorizations of the types of approaches we'll discuss here.

Categories of Machine Leaning

At the most fundamental level, machine learning can be categorized into two main types: supervised learning and unsupervised learning.

Supervised learning involves somehow modeling the relationship between measured features of data and some label associated with the data; once this model is determined, it can be used to apply labels to new, unknown data. This is further subdivided into classification tasks and regression tasks: in classification, the labels are discrete categories, while in regression, the labels are continuous quantities. We will see examples of both types of supervised learning in the following section.

Unsupervised learning involves modelling the features of a dataset without reference to any label and is often described as "letting the dataset speak for itself." These models include tasks such as clustering and dimensionality reduction. Clustering algorithms identify distinct groups of data, while dimensionality reduction algorithms search for more succinct representations of the data. We will see examples of both types of unsupervised learning in the following section.

Need for Machine Learning

Human beings, at this moment, are the most intelligent and advanced species on earth because they can think, evaluate, and solve complex problems. On the other side, AI is still in its initial stage and have not surpassed human intelligence in many aspects. Then the question is that what is the need to make machine learn? The most suitable reason for doing this is, “to make decisions, based on data, with efficiency and scale”.

Lately, organizations are investing heavily in newer technologies like Artificial Intelligence, Machine Learning and Deep Learning to get the key information from data to perform several real-world tasks and solve problems. We can call it data-driven decisions taken by machines, particularly to automate the process. These data-driven decisions can be used, instead of using programing logic, in the problems that cannot be programmed inherently. The fact is that we can’t do without human intelligence, but other aspect is that we all need to solve real-world problems with efficiency at a huge scale. That is why the need for machine learning arises.

Challenges in Machines Learning

While Machine Learning is rapidly evolving, making significant strides with cybersecurity and autonomous cars, this segment of AI as whole still has a long way to go. The reason behind is that ML has not been able to overcome number of challenges. The challenges that ML is facing currently are −

1. Quality of data − Having good-quality data for ML algorithms is one of the biggest challenges. Use of low-quality data leads to the problems related to data preprocessing and feature extraction.
2. Time-Consuming task − Another challenge faced by ML models is the consumption of time especially for data acquisition, feature extraction and retrieval.

3. Lack of specialist persons − As ML technology is still in its infancy stage, availability of expert resources is a tough job.
4. No clear objective for formulating business problems − Having no clear objective and well-defined goal for business problems is another key challenge for ML because this technology is not that mature yet.
5. Issue of overfitting & underfitting − If the model is overfitting or underfitting, it cannot be represented well for the problem.
6. Curse of dimensionality − Another challenge ML model faces is too many features of data points. This can be a real hindrance.
7. Difficulty in deployment − Complexity of the ML model makes it quite difficult to be deployed in real life.

Applications of Machines Learning

Machine Learning is the most rapidly growing technology and according to researchers we are in the golden year of AI and ML. It is used to solve many real-world complex problems which cannot be solved with traditional approach. Following are some real-world applications of ML.

- Emotion analysis
- Sentiment analysis
- Error detection and prevention
- Weather forecasting and prediction
- Stock market analysis and forecasting
- Speech synthesis
- Speech recognition
- Customer segmentation
- Object recognition
- Fraud detection
- Fraud prevention
- Recommendation of products to customer in online shopping

How to Start Learning Machine Learning?

Arthur Samuel coined the term “Machine Learning” in 1959 and defined it as a “Field of study that gives computers the capability to learn without being explicitly programmed”.

And that was the beginning of Machine Learning! In modern times, Machine Learning is one of the most popular (if not the most!) career choices. According to Indeed, Machine Learning Engineer Is the Best Job of 2019 with a 344% growth and an average base salary of $146,085 per year.

But there is still a lot of doubt about what exactly is Machine Learning and how to start learning it? So, this article deals with the Basics of Machine Learning and also the path you can follow to eventually become a full-fledged Machine Learning Engineer. Now let's get started!!!

How to start learning ML?

This is a rough roadmap you can follow on your way to becoming an insanely talented Machine Learning Engineer. Of course, you can always modify the steps according to your needs to reach your desired end-goal!

Step 1 – Understand the Prerequisites

In case you are a genius, you could start ML directly but normally, there are some prerequisites that you need to know which include Linear Algebra, Multivariate Calculus, Statistics, and Python. And if you don't know these, never fear! You don't need a Ph.D. degree in these topics to get started but you do need a basic understanding.

(a) Learn Linear Algebra and Multivariate Calculus

Both Linear Algebra and Multivariate Calculus are important in Machine Learning. However, the extent to which you need them depends on your role as a data scientist. If you are more focused on application heavy machine learning, then you will not be that heavily focused on maths as there are many common libraries available. But if you want to focus on R&D in Machine Learning, then mastery of Linear Algebra and Multivariate Calculus is very important as you will have to implement many ML algorithms from scratch.

(b) Learn Statistics

Data plays a huge role in Machine Learning. In fact, around 80% of your time as an ML expert will be spent collecting and cleaning data. And statistics is a field that handles the collection, analysis, and presentation of data. So it is no surprise that you need to learn it!!!

Some of the key concepts in statistics that are important are Statistical Significance, Probability Distributions, Hypothesis Testing, Regression, etc. Also, Bayesian Thinking is also a very important part of ML which deals with various concepts like Conditional Probability, Priors, and Posteriors, Maximum Likelihood, etc.

(c) Learn Python

Some people prefer to skip Linear Algebra, Multivariate Calculus and Statistics and learn them as they go along with trial and error. But the one thing that you absolutely cannot skip is Python! While there are other languages you can use for Machine Learning like R, Scala, etc. Python is currently the most popular language for ML. In fact, there are many Python libraries that are specifically useful for Artificial Intelligence and Machine Learning such as Keras, TensorFlow, Scikit-learn, etc.

So, if you want to learn ML, it's best if you learn Python! You can do that using various online resources and courses such as Fork Python available Free on GeeksforGeeks.

Step 2 – Learn Various ML Concepts

Now that you are done with the prerequisites, you can move on to actually learning ML (Which is the fun part!!!) It's best to start with the basics and then move on to the more complicated stuff. Some of the basic concepts in ML are:

(a) Terminologies of Machine Learning

- Model – A model is a specific representation learned from data by applying some machine learning algorithm. A model is also called a hypothesis.
- Feature – A feature is an individual measurable property of the data. A set of numeric features can be conveniently described by a feature vector. Feature vectors are fed as input to the model. For example, in order to predict a fruit, there may be features like color, smell, taste, etc.
- Target (Label) – A target variable or label is the value to be predicted by our model. For the fruit example discussed in the feature section, the label with each set of input would be the name of the fruit like apple, orange, banana, etc.
- Training – The idea is to give a set of inputs(features) and it's expected outputs(labels), so after training, we will have a model (hypothesis) that will then map new data to one of the categories trained on.
- Prediction – Once our model is ready, it can be fed a set of inputs to which it

will provide a predicted output(label).

(b) Types of Machine Learning

- Supervised Learning – This involves learning from a training dataset with labeled data using classification and regression models. This learning process continues until the required level of performance is achieved.
- Unsupervised Learning – This involves using unlabelled data and then finding the underlying structure in the data in order to learn more and more about the data itself using factor and cluster analysis models.
- Semi-supervised Learning – This involves using unlabelled data like Unsupervised Learning with a small amount of labeled data. Using labeled data vastly increases the learning accuracy and is also more cost-effective than Supervised Learning.
- Reinforcement Learning – This involves learning optimal actions through trial and error. So, the next action is decided by learning behaviors that are based on the current state and that will maximize the reward in the future.

Advantages of Machine learning

1. Easily identifies trends and patterns: Machine Learning can review large volumes of data and discover specific trends and patterns that would not be apparent to humans. For instance, for an e-commerce website like Amazon, it serves to understand the browsing behaviors and purchase histories of its users to help cater to the right products, deals, and reminders relevant to them. It uses the results to reveal relevant advertisements to them.

2. No human intervention needed (automation): With ML, you don't need to babysit your project every step of the way. Since it means giving machines the ability to learn, it lets them make predictions and also improve the algorithms on their own. A common example of this is anti-virus softwares; they learn to filter new threats as they are recognized. ML is also good at recognizing spam.

3. Continuous Improvement: As ML algorithms gain experience, they keep improving in accuracy and efficiency. This lets them make better decisions. Say you need to make a weather forecast model. As the amount of data, you have keeps growing, your algorithms learn to make more accurate predictions faster.

4. Handling multi-dimensional and multi-variety data: Machine Learning algorithms are good at handling data that are multi-dimensional and multi-variety, and they can do this in dynamic or uncertain environments.

5. Wide Applications: You could be an e-tailer or a healthcare provider and make ML work for you. Where it does apply, it holds the capability to help deliver a much more personal experience to customers while also targeting the right customers.

Disadvantages of Machine Learning

1. Data Acquisition: Machine Learning requires massive data sets to train on, and these should be inclusive/unbiased, and of good quality. There can also be times where they must wait for new data to be generated.

2. Time and Resources: ML needs enough time to let the algorithms learn and develop enough to fulfill their purpose with a considerable amount of accuracy and relevancy. It also needs massive resources to function. This can mean additional requirements of computer power for you.

3. Interpretation of Results: Another major challenge is the ability to accurately interpret results generated by the algorithms. You must also carefully choose the algorithms for your purpose.

4. High error-susceptibility: Machine Learning is autonomous but highly susceptible to errors. Suppose you train an algorithm with data sets small enough to not be inclusive. You end up with biased predictions coming from a biased training set. This leads to irrelevant advertisements being displayed to customers. In the case of ML, such blunders can set off a chain of errors that can go undetected for long periods of time. And when they do get noticed, it takes quite some time to recognize the source of the issue, and even longer to correct it

CHAPTER 6

SOFTWARE ENVIRONMENT

What is Python?

Below are some facts about Python.

- Python is currently the most widely used multi-purpose, high-level programming language.
- Python allows programming in Object-Oriented and Procedural paradigms. Python programs generally are smaller than other programming languages like Java.
- Programmers have to type relatively less and indentation requirement of the language, makes them readable all the time.
- Python language is being used by almost all tech-giant companies like – Google, Amazon, Facebook, Instagram, Dropbox, Uber… etc.

The biggest strength of Python is huge collection of standard libraries which can be used for the following –

- Machine Learning
- GUI Applications (like Kivy, Tkinter, PyQt etc.)
- Web frameworks like Django (used by YouTube, Instagram, Dropbox)
- Image processing (like Opencv, Pillow)
- Web scraping (like Scrapy, BeautifulSoup, Selenium)
- Test frameworks
- Multimedia

Advantages of Python

Let's see how Python dominates over other languages.

1. Extensive Libraries

Python downloads with an extensive library and it contain code for various purposes like regular expressions, documentation-generation, unit-testing, web browsers, threading, databases, CGI, email, image manipulation, and more. So, we don't have to write the complete code for that manually.

2. Extensible

As we have seen earlier, Python can be extended to other languages. You can write some of your code in languages like C++ or C. This comes in handy, especially in projects.

3. Embeddable

Complimentary to extensibility, Python is embeddable as well. You can put your Python code in your source code of a different language, like C++. This lets us add scripting capabilities to our code in the other language.

4. Improved Productivity

The language's simplicity and extensive libraries render programmers more productive than languages like Java and C++ do. Also, the fact that you need to write less and get more things done.

5. IOT Opportunities

Since Python forms the basis of new platforms like Raspberry Pi, it finds the future bright for the Internet of Things. This is a way to connect the language with the real world.

6. Simple and Easy

When working with Java, you may have to create a class to print 'Hello World'. But in Python, just a print statement will do. It is also quite easy to learn, understand, and code. This is why when people pick up Python, they have a hard time adjusting to other more verbose languages like Java.

7. Readable

Because it is not such a verbose language, reading Python is much like reading English. This is the reason why it is so easy to learn, understand, and code. It also does not need curly braces to define blocks, and indentation is mandatory. These further aids the readability of the code.

8. Object-Oriented

This language supports both the procedural and object-oriented programming paradigms. While functions help us with code reusability, classes and objects let us model the real world. A class allows the encapsulation of data and functions into one.

9. Free and Open-Source

Like we said earlier, Python is freely available. But not only can you download Python for free, but you can also download its source code, make changes to it, and even distribute it. It downloads with an extensive collection of libraries to help you with your tasks.

10. Portable

When you code your project in a language like C++, you may need to make some changes to it if you want to run it on another platform. But it isn't the same with Python. Here, you need to code only once, and you can run it anywhere. This is called Write Once Run Anywhere (WORA). However, you need to be careful enough not to include any system-dependent features.

11. Interpreted

Lastly, we will say that it is an interpreted language. Since statements are executed one by one, debugging is easier than in compiled languages.

Any doubts till now in the advantages of Python? Mention in the comment section.

Advantages of Python Over Other Languages

1. Less Coding

Almost all of the tasks done in Python requires less coding when the same task is done in other languages. Python also has an awesome standard library support, so you don't have to search for any third-party libraries to get your job done. This is the reason that many people suggest learning Python to beginners.

2. Affordable

Python is free therefore individuals, small companies or big organizations can leverage the free available resources to build applications. Python is popular and widely used so it gives you better community support.

The 2019 Github annual survey showed us that Python has overtaken Java in the most popular programming language category.

3. Python is for Everyone

Python code can run on any machine whether it is Linux, Mac or Windows. Programmers need to learn different languages for different jobs but with Python, you can professionally build web apps, perform data analysis and machine learning, automate things, do web scraping and also build games and powerful visualizations. It is an all-rounder programming language.

Disadvantages of Python

So far, we've seen why Python is a great choice for your project. But if you choose it, you should be aware of its consequences as well. Let's now see the downsides of choosing Python over another language.

1. Speed Limitations

We have seen that Python code is executed line by line. But since Python is interpreted, it often results in slow execution. This, however, isn't a problem unless speed is a focal point for the project. In other words, unless high speed is a requirement, the benefits offered by Python are enough to distract us from its speed limitations.

2. Weak in Mobile Computing and Browsers

While it serves as an excellent server-side language, Python is much rarely seen on the client-side. Besides that, it is rarely ever used to implement smartphone-based applications. One such application is called Carbonnelle.

The reason it is not so famous despite the existence of Brython is that it isn't that secure.

3. Design Restrictions

As you know, Python is dynamically-typed. This means that you don't need to declare the type of variable while writing the code. It uses duck-typing. But wait, what's that? Well, it just means that if it looks like a duck, it must be a duck. While this is easy on the programmers during coding, it can raise run-time errors.

4. Underdeveloped Database Access Layers

Compared to more widely used technologies like JDBC (Java DataBase Connectivity) and ODBC (Open DataBase Connectivity), Python’s database access layers are a bit underdeveloped. Consequently, it is less often applied in huge enterprises.

5. Simple

No, we’re not kidding. Python’s simplicity can indeed be a problem. Take my example. I don’t do Java, I’m more of a Python person. To me, its syntax is so simple that the verbosity of Java code seems unnecessary.

This was all about the Advantages and Disadvantages of Python Programming Language.

History of Python

What do the alphabet and the programming language Python have in common? Right, both start with ABC. If we are talking about ABC in the Python context, it's clear that the programming language ABC is meant. ABC is a general-purpose programming language and programming environment, which had been developed in the Netherlands, Amsterdam, at the CWI (Centrum Wiskunde &Informatica). The greatest achievement of ABC was to influence the design of Python. Python was conceptualized in the late 1980s. Guido van Rossum worked that time in a project at the CWI, called Amoeba, a distributed operating system. In an interview with Bill Venners[1], Guido van Rossum said: "In the early 1980s, I worked as an implementer on a team building a language called ABC at Centrum voor Wiskunde en Informatica (CWI). I don't know how well people know ABC's influence on Python. I try to mention ABC's influence because I'm indebted to everything I learned during that project and to the people who worked on it. "Later on in the same Interview, Guido van Rossum continued: "I remembered all my experience and some of my frustration with ABC. I decided to try to design a simple scripting language that possessed some of ABC's better properties, but without its problems. So I started typing. I created a simple virtual machine, a simple parser, and a simple runtime. I made my own version of the various ABC parts that I liked. I created a basic syntax, used indentation for statement grouping instead of curly braces or begin-end blocks, and developed a small number of powerful data types: a hash table (or dictionary, as we call it), a list, strings, and numbers."

Python Development Steps

Guido Van Rossum published the first version of Python code (version 0.9.0) at alt.sources in February 1991. This release included already exception handling, functions, and the core data types of lists, dict, str and others. It was also object oriented and had a module system.
Python version 1.0 was released in January 1994. The major new features included in this release were the functional programming tools lambda, map, filter and reduce, which Guido Van Rossum never liked. Six and a half years later in October 2000, Python 2.0 was introduced. This release included list comprehensions, a full garbage collector and it was supporting unicode. Python flourished for another 8 years in the versions 2.x before the next major release as Python 3.0 (also known as "Python 3000" and "Py3K") was released. Python 3 is not backwards compatible with Python 2.x. The emphasis in Python 3 had been on the removal of duplicate programming constructs and modules, thus fulfilling or coming close to fulfilling the 13th law of the Zen of Python: "There should be one -- and preferably only one -- obvious way to do it."Some changes in Python 7.3:

- Print is now a function.
- Views and iterators instead of lists
- The rules for ordering comparisons have been simplified. E.g., a heterogeneous list cannot be sorted, because all the elements of a list must be comparable to each other.
- There is only one integer type left, i.e., int. long is int as well.
- The division of two integers returns a float instead of an integer. "//" can be used to have the "old" behaviour.
- Text Vs. Data Instead of Unicode Vs. 8-bit

Purpose

We demonstrated that our approach enables successful segmentation of intra-retinal layers—even with low-quality images containing speckle noise, low contrast, and different intensity ranges throughout—with the assistance of the ANIS feature.

Python

Python is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, notably using significant whitespace.

Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library.

- Python is Interpreted − Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP.
- Python is Interactive − you can actually sit at a Python prompt and interact with the interpreter directly to write your programs.

Python also acknowledges that speed of development is important. Readable and terse code is part of this, and so is access to powerful constructs that avoid tedious repetition of code. Maintainability also ties into this may be an all but useless metric, but it does say something about how much code you have to scan, read and/or understand to troubleshoot problems or tweak behaviors. This speed of development, the ease with which a programmer of other languages can pick up basic Python skills and the huge standard library is key to another area where Python excels. All its tools have been quick to implement, saved a lot of time, and several of them have later been patched and updated by people with no Python background - without breaking.

Modules Used in Project

TensorFlow

TensorFlow is a free and open-source software library for dataflow and differentiable programming across a range of tasks. It is a symbolic math library and is also used for machine learning applications such as neural networks. It is used for both research and production at Google.

TensorFlow was developed by the Google Brain team for internal Google use. It was released under the Apache 2.0 open-source license on November 9, 2015.

NumPy

NumPy is a general-purpose array-processing package. It provides a high-performance multidimensional array object, and tools for working with these arrays.

It is the fundamental package for scientific computing with Python. It contains various features including these important ones:

- A powerful N-dimensional array object
- Sophisticated (broadcasting) functions
- Tools for integrating C/C++ and Fortran code
- Useful linear algebra, Fourier transform, and random number capabilities

Besides its obvious scientific uses, NumPy can also be used as an efficient multi-dimensional container of generic data. Arbitrary datatypes can be defined using NumPy which allows NumPy to seamlessly and speedily integrate with a wide variety of databases.

Pandas

Pandas is an open-source Python Library providing high-performance data manipulation and analysis tool using its powerful data structures. Python was majorly used for data munging and preparation. It had very little contribution towards data analysis. Pandas solved this problem. Using Pandas, we can accomplish five typical steps in the processing and analysis of data, regardless of the origin of data load, prepare, manipulate, model, and analyze. Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc.

Matplotlib

Matplotlib is a Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms. Matplotlib can be used in Python scripts, the Python and IPython shells, the Jupyter Notebook, web application servers, and four graphical user interface toolkits. Matplotlib tries to make easy things easy and hard things possible. You can generate plots, histograms, power spectra, bar charts, error charts, scatter plots, etc., with just a few lines of code. For examples, see the sample plots and thumbnail gallery.

For simple plotting the pyplot module provides a MATLAB-like interface, particularly when combined with IPython. For the power user, you have full control of line styles, font properties, axes properties, etc, via an object-oriented interface or via a set of functions familiar to MATLAB users.

Scikit – learn

Scikit-learn provides a range of supervised and unsupervised learning algorithms via a consistent interface in Python. It is licensed under a permissive simplified BSD license and is distributed under many Linux distributions, encouraging academic and commercial use. Python

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Install Python Step-by-Step in Windows and Mac

Python a versatile programming language doesn't come pre-installed on your computer devices. Python was first released in the year 1991 and until today it is a very popular high-level programming language. Its style philosophy emphasizes code readability with its notable use of great whitespace.

The object-oriented approach and language construct provided by Python enables programmers to write both clear and logical code for projects. This software does not come pre-packaged with Windows.

How to Install Python on Windows and Mac

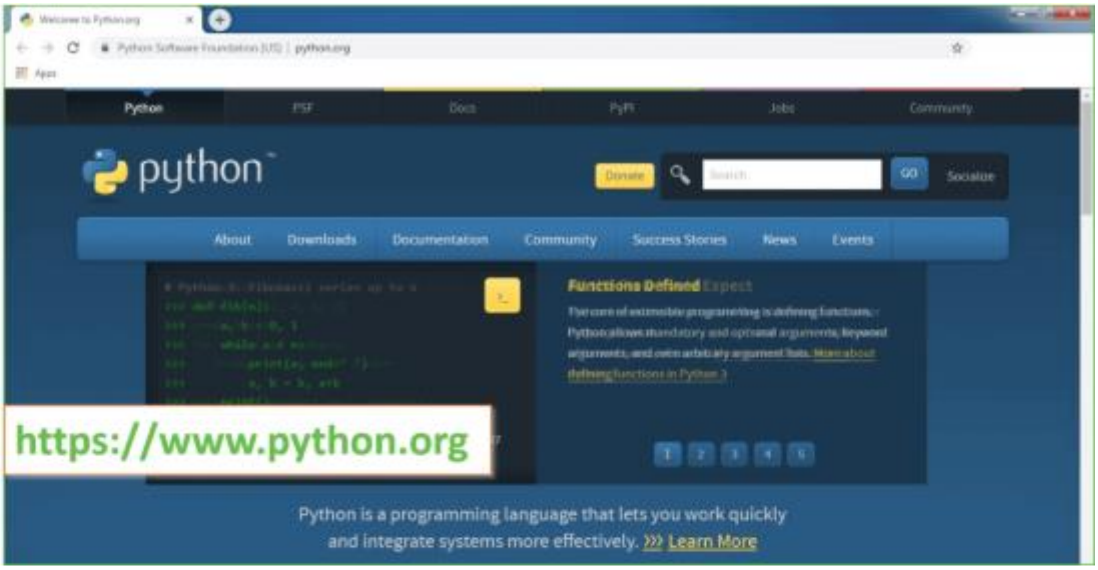
There have been several updates in the Python version over the years. The question is how to install Python? It might be confusing for the beginner who is willing to start learning Python but this tutorial will solve your query. The latest or the newest version of Python is version 3.7.4 or in other words, it is Python 3.

Note: The python version 3.7.4 cannot be used on Windows XP or earlier devices.

Before you start with the installation process of Python. First, you need to know about your System Requirements. Based on your system type i.e., operating system and based processor, you must download the python version. My system type is a Windows 64-bit operating system. So the steps below are to install python version 3.7.4 on Windows 7 device or to install Python 3. Download the Python Cheatsheet here. The steps on how to install Python on Windows 10, 8 and 7 are divided into 4 parts to help understand better.

Download the Correct version into the system

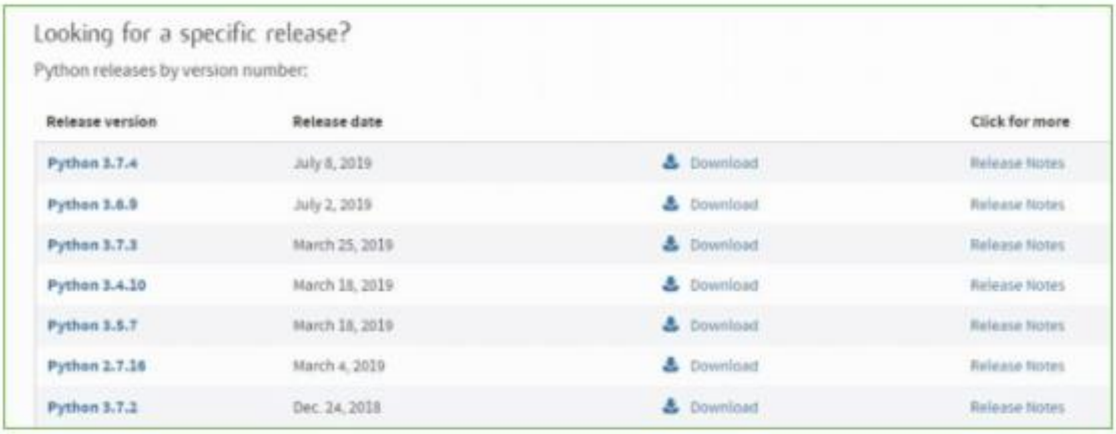
Step 1: Go to the official site to download and install python using Google Chrome or any other web browser. OR Click on the following link: https://www.python.org



Now, check for the latest and the correct version for your operating system.

Step 2: Click on the Download Tab.

Step 3: You can either select the Download Python for windows 3.7.4 button in Yellow Color or you can scroll further down and click on download with respective to their version. Here, we are downloading the most recent python version for windows 3.7.4



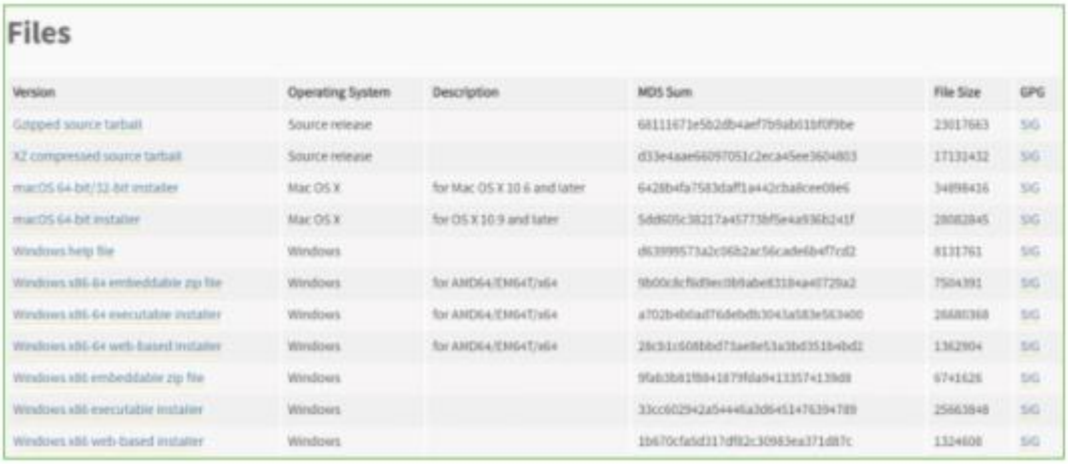
Looking for a specific release?

Python releases by version number:

Release version	Release date		Click for more
Python 3.7.4	July 8, 2019	Download	Release Notes
Python 3.6.9	July 2, 2019	Download	Release Notes
Python 3.7.3	March 25, 2019	Download	Release Notes
Python 3.4.10	March 18, 2019	Download	Release Notes
Python 3.5.7	March 18, 2019	Download	Release Notes
Python 2.7.16	March 4, 2019	Download	Release Notes
Python 3.7.2	Dec. 24, 2018	Download	Release Notes

Step 4: Scroll down the page until you find the Files option.

Step 5: Here you see a different version of python along with the operating system.



Files

Version	Operating System	Description	MD5 Sum	File Size	GPG
Gzipped source tarball	Source release		68111671e5b2db4aef7b9ab01bf0f9be	23017663	SIG
XZ compressed source tarball	Source release		d33e4aae66097051c2eca45ee3604803	17131432	SIG
macOS 64-bit/32-bit installer	Mac OS X	for Mac OS X 10.6 and later	6428b4fa7583daff1a442cba8cee08e6	34898416	SIG
macOS 64-bit installer	Mac OS X	for OS X 10.9 and later	5dd605c38217a45773bf5e4a936b241f	28082845	SIG
Windows help file	Windows		d63999573a2c06b2ac56cade6b4f7cd2	8131761	SIG
Windows x86-64 embeddable zip file	Windows	for AMD64/EM64T/x64	9b00c8cf6d9ec0b9abe83184a40729a2	7504391	SIG
Windows x86-64 executable installer	Windows	for AMD64/EM64T/x64	a702b4b0ad76debdb3043a583e563400	26680368	SIG
Windows x86-64 web-based installer	Windows	for AMD64/EM64T/x64	28cb1c608bbd73ae8e53a3bd351b4bd2	1362904	SIG
Windows x86 embeddable zip file	Windows		9fab3b81f8841879fda94133574139d8	6741626	SIG
Windows x86 executable installer	Windows		33cc602942a54446a3d6451476394789	25663848	SIG
Windows x86 web-based installer	Windows		1b670cfa5d317df82c30983ea371d87c	1324608	SIG

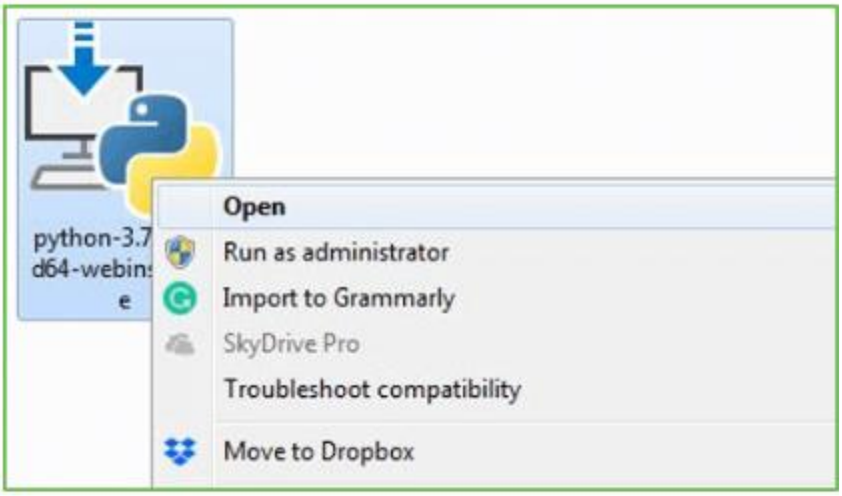
- To download Windows 32-bit python, you can select any one from the three options: Windows x86 embeddable zip file, Windows x86 executable installer or Windows x86 web-based installer.
- To download Windows 64-bit python, you can select any one from the three options: Windows x86-64 embeddable zip file, Windows x86-64 executable installer or Windows x86-64 web-based installer.

Here we will install Windows x86-64 web-based installer. Here your first part regarding which version of python is to be downloaded is completed. Now we move ahead with the second part in installing python i.e., Installation

Note: To know the changes or updates that are made in the version you can click on the Release Note Option.

Installation of Python

Step 1: Go to Download and Open the downloaded python version to carry out the installation process.



Step 2: Before you click on Install Now, Make sure to put a tick on Add Python 3.7 to PATH.

Step 3: Click on Install NOW After the installation is successful. Click on Close.

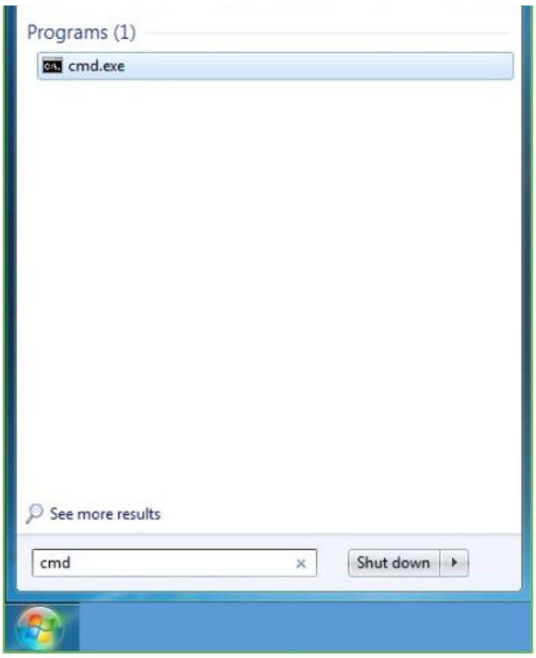
With these above three steps on python installation, you have successfully and correctly installed Python. Now is the time to verify the installation.

Note: The installation process might take a couple of minutes.

Verify the Python Installation

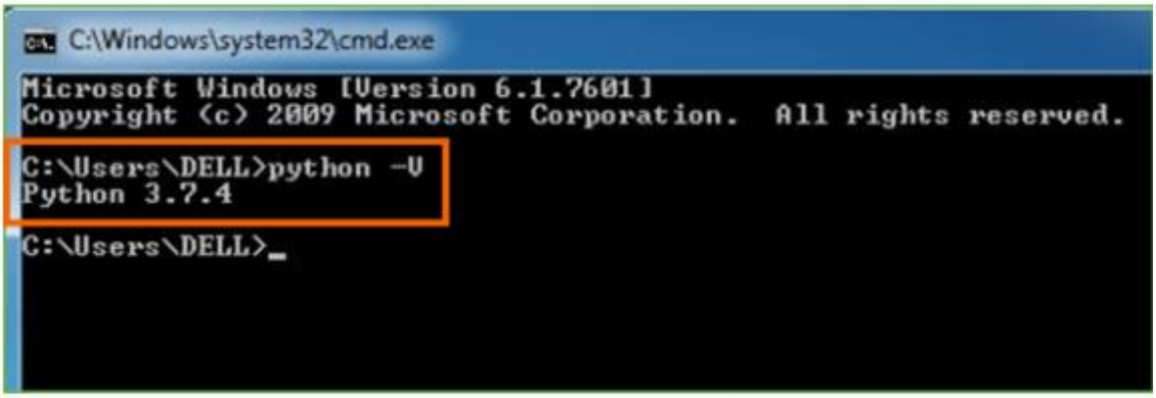
Step 1: Click on Start

Step 2: In the Windows Run Command, type "cmd".



Step 3: Open the Command prompt option.

Step 4: Let us test whether the python is correctly installed. Type python –V and press Enter.



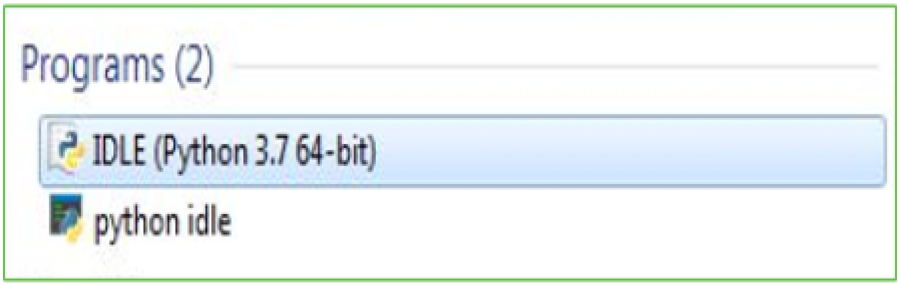
Step 5: You will get the answer as 3.7.4

Note: If you have any of the earlier versions of Python already installed. You must first uninstall the earlier version and then install the new one.

Check how the Python IDLE works

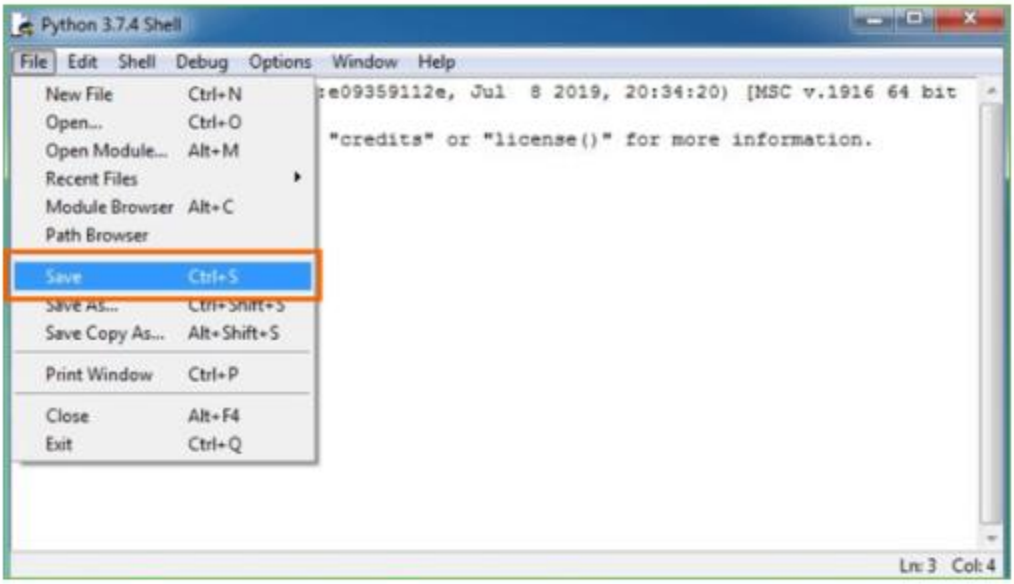
Step 1: Click on Start

Step 2: In the Windows Run command, type "python idle".



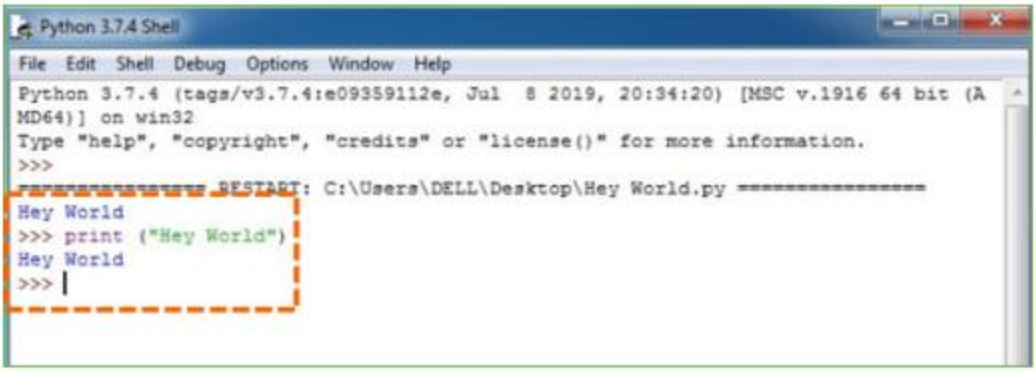
Step 3: Click on IDLE (Python 3.7 64-bit) and launch the program

Step 4: To go ahead with working in IDLE you must first save the file. Click on File > Click on Save



Step 5: Name the file and save as type should be Python files. Click on SAVE. Here I have named the files as Hey World.

Step 6: Now for e.g. enter print ("Hey World") and Press Enter.



You will see that the command given is launched. With this, we end our tutorial on how to install Python. You have learned how to download python for windows into your respective operating system.

Note: Unlike Java, Python does not need semicolons at the end of the statements otherwise it won't work.

Chapter 7

Source Code:

```
import pandas as pd

import os

from skimage.transform import resize

from skimage.io import imread

import numpy as np

import matplotlib.pyplot as plt

from sklearn import svm

from sklearn.naive_bayes import GaussianNB, MultinomialNB, BernoulliNB

from sklearn.ensemble import RandomForestClassifier

from sklearn.datasets import load_iris

from sklearn.model_selection import GridSearchCV

from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score

from sklearn.metrics import precision_score

from sklearn.metrics import recall_score

from sklearn.metrics import f1_score

from sklearn.metrics import classification_report

from sklearn.metrics import confusion_matrix

import joblib

import seaborn as sns

from skimage import io, transform

from sklearn import preprocessing

import cv2

import tkinter as tk
```

```
from tkinter import *
from tkinter import filedialog
from PIL import ImageTk,Image
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
main=tk.Tk()
main.title("Pneumonia Detection")
main.geometry("1650x1000")
main.config(bg='teal')
menubar=Menu(main)
file = Menu(menubar, tearoff = 0)
menubar.add_cascade(label ='File', menu = file)
file.add_command(label ='New File', command = None)
file.add_command(label ='Open...', command = None)
file.add_command(label ='Save', command = None)
file.add_separator()
file.add_command(label ='Exit', command = main.destroy)
edit = Menu(menubar, tearoff = 0)
menubar.add_cascade(label ='Edit', menu = edit)
edit.add_command(label ='Cut', command = None)
edit.add_command(label ='Copy', command = None)
edit.add_command(label ='Paste', command = None)
edit.add_command(label ='Select All', command = None)
```

```
edit.add_separator()
edit.add_command(label ='Find...', command = None)
edit.add_command(label ='Find again', command = None)
# Adding Help Menu
help_ = Menu(menubar, tearoff = 0)
menubar.add_cascade(label ='Help', menu = help_)
help_.add_command(label ='Tk Help', command = None)
help_.add_command(label ='Demo', command = None)
help_.add_separator()
help_.add_command(label ='About Tk', command = None)
# display Menu
main.config(menu = menubar)
image = Image.open(r"C:\Users\m.sumanth\Downloads\pexels-timotej-nagy-284951.jpg")
image = image.resize((1650, 1000), Image.ANTIALIAS)
photo = ImageTk.PhotoImage(image)
#Create a label with the image as background
background_label = tk.Label(main, image=photo)
background_label.place(x=0, y=0, relwidth=1, relheight=1)
title=tk.Label(main, text="Pneumonia Detection",justify='center')
def upload():
    global categories
    filename=filedialog.askdirectory(initialdir=".")
    path=filename
    model_folder='model'
    categories=[d for d in os.listdir(path) if os.path.isdir(os.path.join(path,d))]
```

```
    text.delete('1.0',END)
    text.insert(END,"Dataset Loaded Successfully. \n\n")
    text.insert(END,"Total categories found in the dataset"+str(categories)+'\n\n')
def preprocess():
    global X,Y
    global model_folder
    path=r"dataset"
    model_folder='model'
    categories=[d for d in os.listdir(path) if os.path.isdir(os.path.join(path,d))]
    X_file = os.path.join(model_folder, "X.npy")
    Y_file = os.path.join(model_folder, "Y.npy")
    if os.path.exists(X_file) and os.path.exists(Y_file):
        X = np.load(X_file)
        Y = np.load(Y_file)
        text.delete('1.0',END)
        text.insert(END,"Total images found in the dataset  :  "+str(X.shape[0])+'\n\n')
        text.insert(END,"Total categories found in the dataset : "+str(categories)+'\n\n')
    else:
        X =[]#input array
        Y =[]#output array
        for i in categories:
            text.delete('1.0',END)
            text.insert(END,f'Loading category:{i}\n\n')
            category_path=os.path.join(path,i)
            for img in os.listdir(category_path):
                img_array=imread(os.path.join(category_path, img))
```

```
            img_resized=resize(img_array,(256,256,3))
            X.append(img_resized.flatten())
            Y.append(categories.index(i))
            text.insert(END,f'Loaded image:{img}successfully\n\n')
        text.insert(END,f'Loaded category: {i} sucessfully\n\n')
    os.makedirs(model_folder)
    np.save(X_file,X)
    np.save(Y_file,Y)
    text.insert(END,"image precessing  done succesufully")
    text.insert(END,"Total images found in the dataset  : "+str(X.shape[0]))
    text.insert(END,"Total categories found in the dataset : "+str(categories)
def data_splitting():
    global X_train,X_test,Y_train,Y_test
    text.delete('1.0',END)
    X_file = os.path.join(model_folder, "X.npy")
    Y_file = os.path.join(model_folder, "Y.npy")
    if os.path.exists(X_file) and os.path.exists(Y_file):
        X = np.load(X_file)
        Y = np.load(Y_file)
        text.delete('1.0',END)
        text.insert(END,"X and Y arrays loaded successfully.\n\n")
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.20,random_state=77)
        text.insert(END,"Total images found in the dataset :
"+str(X_train.shape[0])+"\n")
        text.insert(END,"Total images found in the dataset :
"+str(X_test.shape[0])+'\n')
    else:
```

```
        X =[]#input array
        Y =[]#output array
        text.delete('1.0',END)
        for i in categories:
            text.insert(END,f'Loading category:{i}\n\n')
            category_path=os.path.join(path,i)
            for img in os.listdir(category_path):
                img_array=imread(os.path.join(category_path, img))
                img_resized=resize(img_array,(256,256,3))
                X.append(img_resized.flatten())
                Y.append(categories.index(i))
                text.insert(END,f'Loaded image:{img} succesfully\n\n')
            text.insert(END,f'Loaded category: {i} sucesfully\n\n')
        os.makedirs(model_folder)
        np.save(X_file,X)
        np.save(Y_file,Y)
def navibayes():
    #check if the pkl file exists
    Model_file = os.path.join(model_folder,"NBC_Model.pkl")
    text.delete('1.0',END)
    if os.path.exists(Model_file):
        #load the model from the pkl file
        nb_classifier = joblib.load(Model_file)
        y_pred = nb_classifier.predict(X_test)
        accuracy = accuracy_score(Y_test,y_pred)
        report = classification_report(Y_test, y_pred, target_names=categories)
```

```
    # Print the classification report
    text.insert(END,'  Report for Gaussian Navi_Bayes : \n\n')
    text.insert(END,str(report)+'\n')
    text.insert(END,"Data trained successfully\n\n")
    accuracy = accuracy_score(Y_test, y_pred)*100
    precision = precision_score(Y_test, y_pred, average='weighted')*100
    recall = recall_score(Y_test, y_pred, average='weighted')*100
    f1 = f1_score(Y_test, y_pred, average='weighted')*100
    text.insert(END,f'Accuracy: {accuracy:.3f}\n')
    text.insert(END,f'Precision: {precision:.3f}\n')
    text.insert(END,f'Recall: {recall:.3f}\n')
    text.insert(END,f'F1 Score: {f1:.3f}\n')
else:
    #Create a gaussian Naivebayes classifier
    nb_classifier= BernoulliNB()
    #train the classifier on the training data
    nb_classifier.fit(X_train,Y_train)
    joblib.dump(nb_classifier, Model_file)
    y_pred = nb_classifier.predict(X_test)
    accuracy = accuracy_score(Y_test,y_pred)
    report = classification_report(Y_test, y_pred, target_names=categories)
    text.delete('1.0',END)
    # Print the classification report
    text.insert(END,'  Report for Gaussian Navi_Bayes : \n\n')
    text.insert(END,str(report)+'\n')
    text.insert(END,"Data trained successfully\n\n")
```

```
        accuracy = accuracy_score(Y_test, y_pred)*100
        precision = precision_score(Y_test, y_pred, average='weighted')*100
        recall = recall_score(Y_test, y_pred, average='weighted')*100
        f1 = f1_score(Y_test, y_pred, average='weighted')*100
        text.insert(END,f'Accuracy: {accuracy:.3f}\n')
        text.insert(END,f'Precision: {precision:.3f}\n')
        text.insert(END,f'Recall: {recall:.3f}\n')
        text.insert(END,f'F1 Score: {f1:.3f}\n')
def rfc():
    global model1
    text.delete('1.0',END)
    text.insert(END,'  Report for Random Forest Classification : \n\n')
    model1=RandomForestClassifier()
    model1.fit(X_train,Y_train)
    y_pre=model1.predict(X_test)
    report1 = classification_report(Y_test, y_pre, target_names=categories)
    accuracy_rfc = accuracy_score(Y_test, y_pre)*100
    precision_rfc = precision_score(Y_test, y_pre, average='weighted')*100
    recall_rfc = recall_score(Y_test, y_pre, average='weighted')*100
    f1_rfc = f1_score(Y_test, y_pre, average='weighted')*100
    text.insert(END,"Data trained successfully\n\n")
    text.insert(END,str(report1)+'\n')
    text.insert(END,f'Accuracy: {accuracy_rfc:.3f}\n')
    text.insert(END,f'Precision: {precision_rfc:.3f}\n')
    text.insert(END,f'Recall: {recall_rfc:.3f}\n')
    text.insert(END,f'F1 Score: {f1_rfc:.3f}\n')
```

```
    #y_acc=accuracy_score(Y_test,y_pre)*100
    #text.insert(END,str(y_acc))
    cm = confusion_matrix(Y_test, y_pre)
    class_names=categories
    # Create a heatmap of the confusion matrix
    sns.heatmap(cm, annot=True, cmap="Blues",
xticklabels=class_names,yticklabels=class_names,fmt='d')
    # Set the axis labels and title
    plt.xlabel("Predicted Class")
    plt.ylabel("True class")
    plt.title("Confusion Matrix")
    # Display the heatmap
    plt.show()
def test1():
    global Test_img1
    Test_img1=filedialog.askopenfilename(initialdir=".")
    img=imread(Test_img1)
    img_resize=resize(img,(256,256,3))
    img_preprocessed = [img_resize.flatten()]
    text.delete('1.0',END)
    text.insert(END,Test_img1+'Image loaded Successfully.\n\n')
    #img=cv2.cvtColor(img,cv2.COLOR_RGB2LAB)
    #img=cv2.flip(img,-1)
    output_number=model1.predict(img_preprocessed)[0]
    output_name=categories[output_number]
```

```
    plt.imshow(img)
    plt.text(10,10,f'predicted output:{output_name}', color='white',fontsize=12,weight='bold',backgroundcolor='black')
    plt.axis('off')
    plt.show()
title.grid(column=0,row=0)
font=('Algerian',17)
title.config(bg='orange',fg='navy blue')
title.config(font=font)
title.config(height=3,width=110)
title.place(x=0,y=0)
s=Scale(main, from_=0 , to=100)
uploadButton1=Button(main,text="Upload",command=upload)
uploadButton1.place(x=100,y=150)
uploadButton1.config(bg='cyan',font=font,fg='red')
font1=('Bell MT',12,'bold')
text=Text(main,height=16,width=60)
scroll=Scrollbar(text)
text.configure(yscrollcommand=scroll.set,bg='black',fg='light yellow')
text.place(x=730,y=350)
text.config(font=font1)
uploadButton2=Button(main,text="PreProcess",command=preprocess)
uploadButton2.place(x=300,y=150)
uploadButton2.config(bg='green',font=font,fg='yellow')
```

```
uploadButton3=Button(main,text="Splittng",command=data_splitting)
uploadButton3.place(x=560,y=150)
uploadButton3.config(bg='violet',font=font,fg='black')
uploadButton4=Button(main,text="Navi Bayes",command=navibayes)
uploadButton4.place(x=800,y=150)
uploadButton4.config(bg='light green',font=font,fg='green')
uploadButton5=Button(main,text="RFC",command=rfc)
uploadButton5.place(x=1000,y=150)
uploadButton5.config(bg='teal',font=font,fg='aqua')
uploadButton5=Button(main,text="Test2",command=test1)
uploadButton5.place(x=1200,y=150)
uploadButton5.config(bg='blue',font=font,fg='white')
main.mainloop()
```

Chapter 8

8.1Implementation description:

- **Upload Dataset**: Allows users to upload a dataset from their local system. It involves providing a collection of images detection methods. These datasets typically include both normal and diseased images, to help train deep learning models for accurate fire detection.
- **Image Preprocess Dataset**: Involves the use of algorithms to analyze images captured by cameras to detect the presence of fire or fire risk. This process can be based on various color models, such as RGB and YCbCr, to isolate fire pixels from the background and separate luminance and chrominance from the original image. The processed images are then filtered and analyzed to differentiate between fire detection and false detection. This method can be used to reduce false alarms and improve the overall performance of fire detection systems.
- **Data Splitting**: It refers to the process of dividing the dataset into multiple subsets, typically for training, validation, and testing purposes. This is an important aspect of machine learning, as it helps prevent overfitting and ensures that the model is able to generalize well to new, unseen data. In the context of fire detection, the dataset may include images or videos of fire and non-fire scenarios, which are split into training, validation, and testing sets. The training set is used to train the model, the validation set is used to tune hyperparameters and prevent overfitting, and the testing set is used to evaluate the model's performance on unseen data.

Naive Bayes: Naive Bayes is a classification algorithm based on Bayes' theorem that assumes the features are conditionally independent given the class. It is a simple and fast algorithm that can be used for fire detection by analysing the probability of a given dataset belonging to the fire class. The algorithm works by calculating the probability of each class given the input features and then selecting the class with the highest probability. In the context of fire detection, Naive Bayes can be used to classify images or sensor data as either containing a fire or not, based on the features extracted from the data.

8.2 Data set description:

We have obtained a set of pneumonia chest x-rays (203), and we plan to utilize these images to train a machine learning model for pneumonia detection. The x-rays will serve as the primary data source for the development of the algorithm, allowing the machine learning system to learn and identify patterns associated with pneumonia in the images. By leveraging this dataset, we aim to enhance the accuracy and efficiency of pneumonia diagnosis through the application of machine learning technology. In order to train a machine learning model to detect normal chest X-rays, we can use existing chest X-ray data (203) that has been labelled as normal. According to a systematic review of machine learning applications for chest X-rays, there are many open sources of chest X-ray images available for research purposes. One study used a total of 203 normal chest X-ray images to train a machine learning model to classify normal and abnormal chest X-rays. Another study used a dataset of over 406 chest X-rays, including normal and pneumonia cases, to train a deep learning model for chest X-ray analysis. By using these existing datasets of normal chest X-rays, we can train a machine learning model to accurately detect normal cases and potentially improve the efficiency and accuracy of chest X-ray interpretation.

8.3 Result Description:

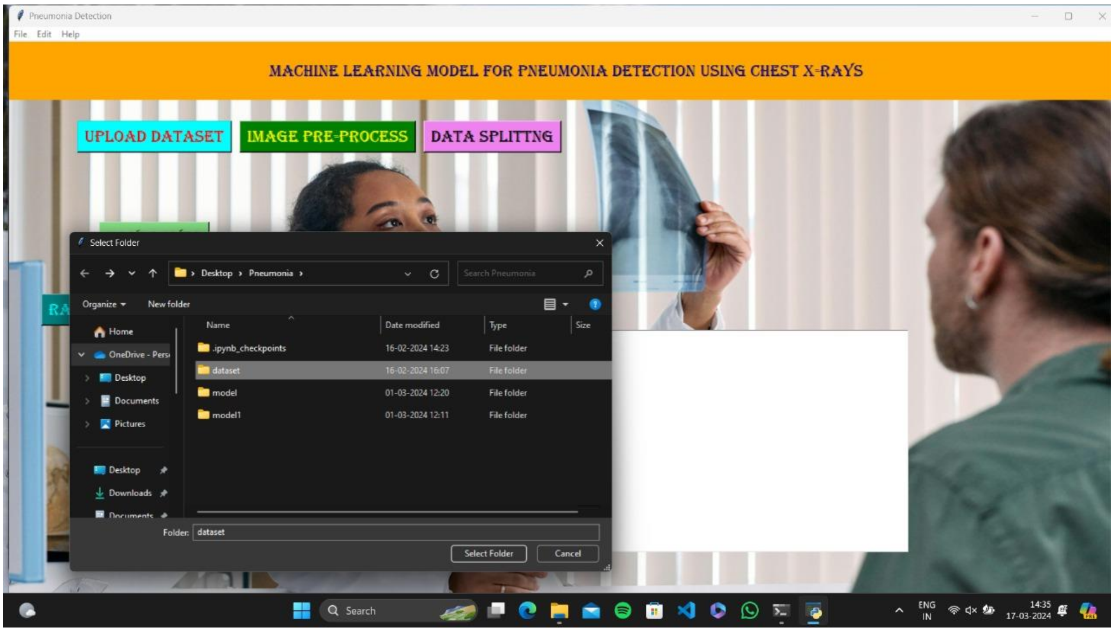


Fig 8.3.1:-Dataset Uploading

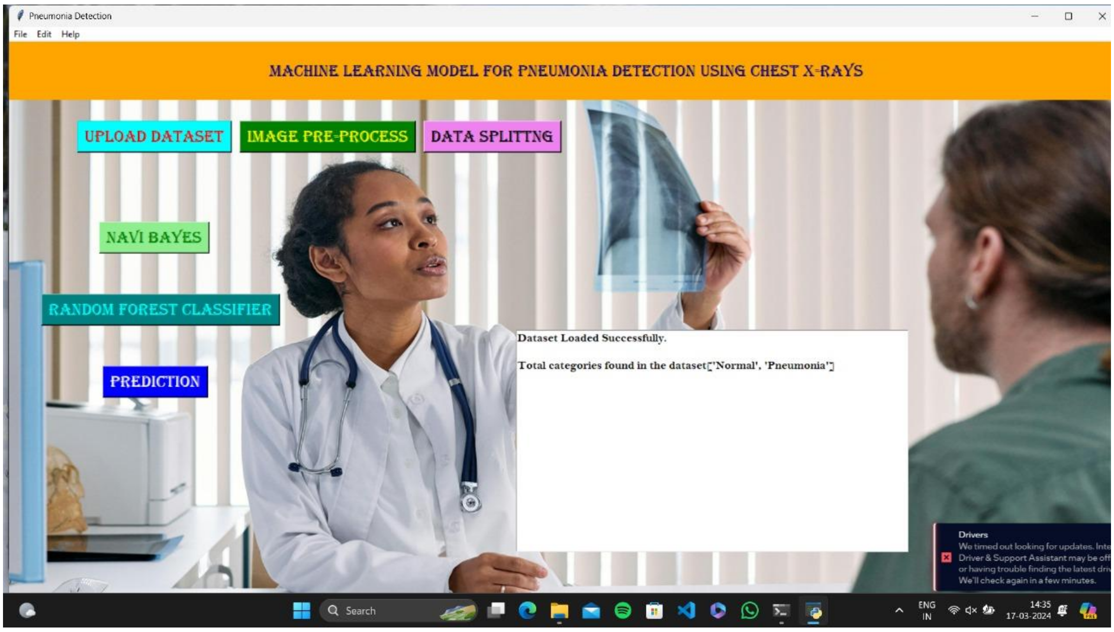


Fig 8.3.2:-Image Pre-Processing

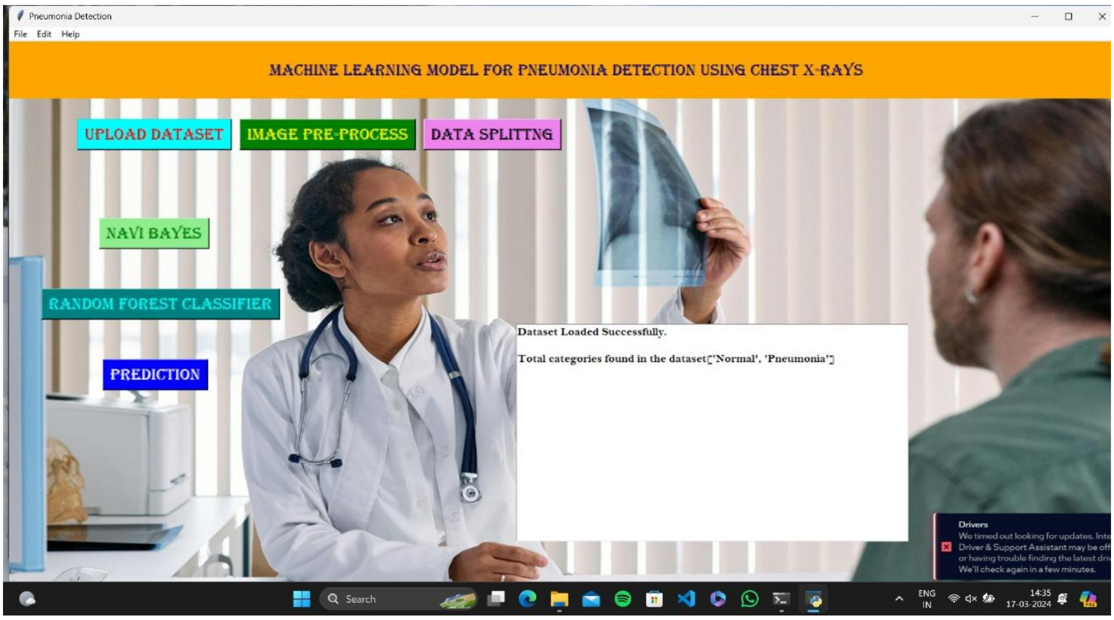


Fig 8.3.3:-Data Splitting

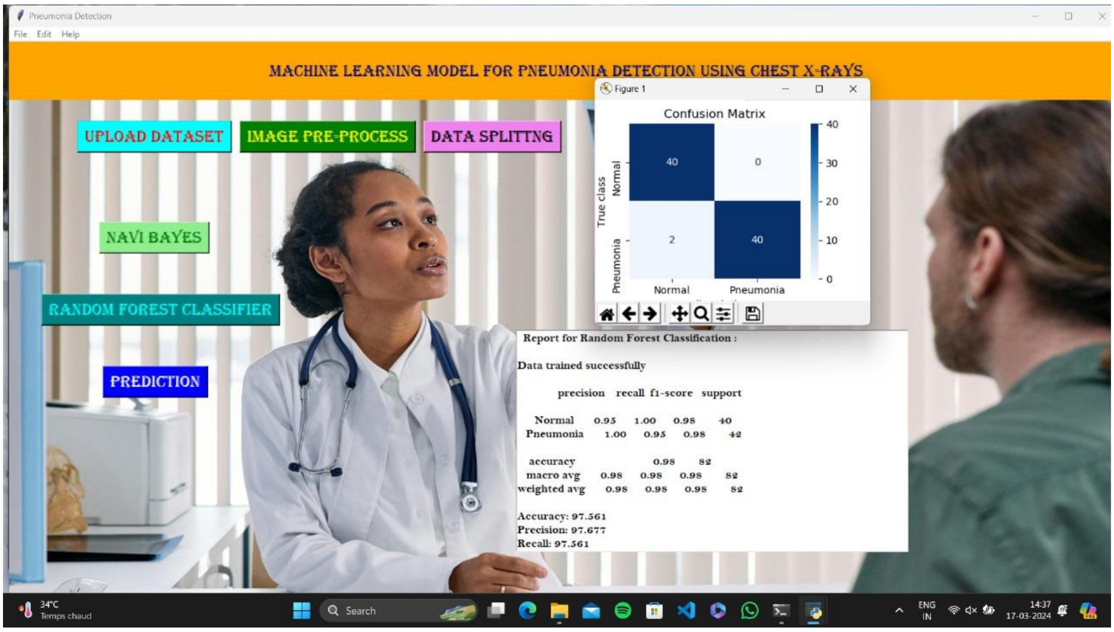


Fig 8.3.4:-Random Forest Classifier Accuracy and confusion matrix

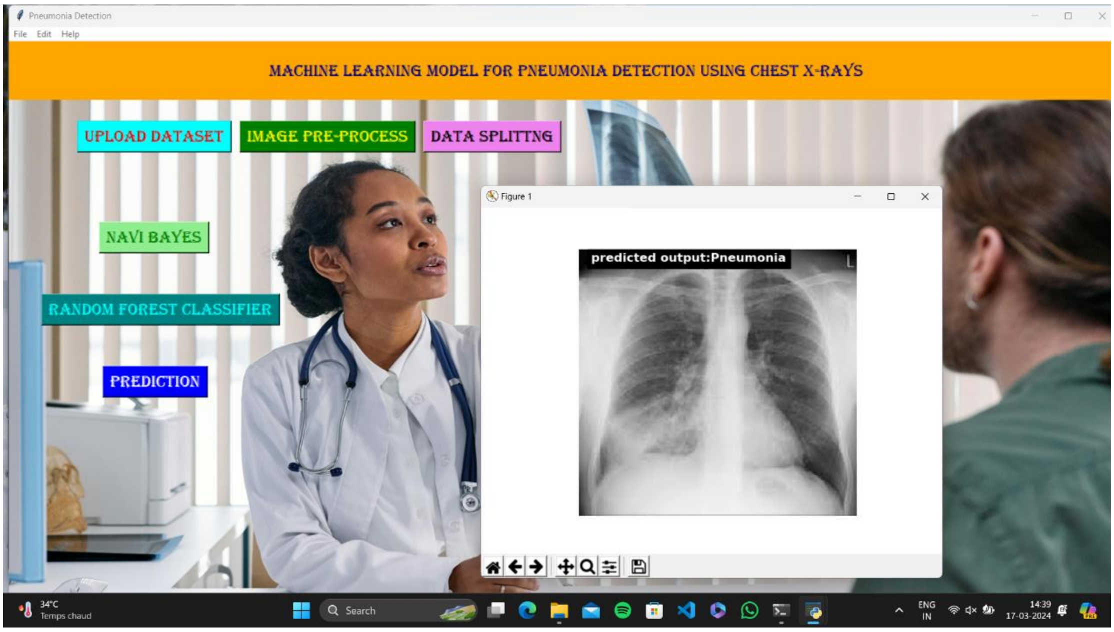


Fig 8.3.1:-Predicted Output

Chapter 9

9.1 Conclusion:

Pneumonia detection using machine learning models has revolutionized the medical field by offering efficient and accurate diagnostic capabilities. Pneumonia, an acute respiratory infection affecting the lungs, poses significant health risks, especially in regions with limited access to healthcare professionals. Pneumonia detection using ML has emerged as a informative technology in the field of medical safety. These systems leverage artificial intelligence to enhance early detection, reduce false assumptions, and provide valuable analytics for risk management. AI-based systems can detect diseases at an earlier stage than traditional detectors. AI algorithms can distinguish between real one and fake more effectively. Early diagnosis of pneumonia is critical for effective treatment and reducing mortality rates associated with the disease. Machine learning-assisted prediction models based on non-invasive measures like biomarkers and physical features have shown promising results in predicting pneumonia accurately In conclusion, the application of machine learning algorithms in pneumonia detection represents a significant advancement in medical diagnostics. These innovative approaches not only enhance diagnostic accuracy but also streamline the detection process, making it more accessible even in resource-constrained settings. The ongoing research focus on improving these models further underscores their potential to revolutionize pneumonia diagnosis and improve patient care outcomes.

9.2 FUTURE SCOPE

The future scope of fire detection pneumonia using chest x rays. The future of pneumonia detection using ML models holds great potential for improving safety measures, reducing response times, and minimizing the impact of fire incidents. As technology advances further, these systems are expected to become more sophisticated, accurate, and seamlessly integrated. The Medical benefits of using ML-enabled pneumonia detection models are significant and contribute to a safer and more sustainable future. The utilization of ML-enabled pneumonia detection models not only enhances safety measures but also plays a crucial role in protecting the environment by enabling early detection, reducing false assumptions, and minimizing the environmental impact of diseases through efficient prevention and response strategies

Chapter 10

10.1References:

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