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MedicHub – Disease Detection Using Deep Learning

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Abstract

The integration of technology in healthcare is rapidly revolutionizing the sector and transforming the traditional modus operandi that used to be followed into a more efficient and accurate automated system. Machine Learning is a sophisticated technology used to analyze clinical symptoms to predict diseases and deliver accurate diagnoses based on strong evidence. The major advantage of using technology to assist in diagnosis is to understand more about underlying illnesses that are often overlooked while searching for a more severe disease, or when the patient is not in imminent danger. This offers patients a very reliable and accessible alternative for immediate results and also minimizes the risk of errors. Another extremely good utility of technology is withinside the discipline of medical image analysis.

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Convolutional Neural Networks (CNN) are neural networks which are capable of recognizing patterns in pictures and hence must be included in the system to increase its accuracy and efficacy. CNN can recognize and identify patterns in medical pictures like X-rays, MRI scans, or CT scans, allowing it to accurately diagnose complicated diseases such as Brain Tumor, COVID-19, Alzheimer's disease, and Pneumonia. With the increasing number of patients and variety of diseases, it is important to handle large datasets efficiently, while maintaining accuracy. The use of CNN to predict illnesses based on symptoms can benefit the patients as well as the medical fraternity as it may assist in expediting the diagnosis and treatment process.

Keywords: Convolutional Neural Network, Real-Time Detection, Magnetic Resonance Imaging, Natural Language Processing

1 Introduction

Healthcare systems are critical to humanity's economic and social well-being. The World has changed dramatically in the last few decades, as has the healthcare sector. Despite advances in technology and medicine, there are still barriers that need to be overcome to ensure that people receive the best possible care.

Doctors and nurses are on the front lines of healthcare, working relentlessly to save lives and provide treatment while frequently placing themselves in danger. Virtual physicians have risen in popularity as an alternative to regular in-person medical checks in recent years. Although this may not always be possible in an emergency, virtual physicians have the potential to relieve pressure on the healthcare system and increase patient access to services.

Virtual physicians using machine learning algorithms may effectively forecast a patient's disease without the need for physical contact. This is especially useful in extreme circumstances like COVID-19 when early discovery can save lives. While virtual doctors are currently available, they lack the precision required to provide accurate predictions.

Image segmentation techniques can also be used to help healthcare providers. An example is detecting brain tumors. Delineating the exact margins of the tumor is critical for effective therapy, and often radiologists struggle with this. By analyzing medical pictures such as CT scans, AI can aid radiologists in properly detecting tumor boundaries. AI algorithms can help identify tumor tissue from healthy brain tissue, lowering the risk of misdiagnosis and helping in surgical planning.

Similarly, early Alzheimer's disease detection is crucial for successful therapy and enhanced patient outcomes. Current diagnostic approaches rely on subjective cognitive exams, which are inefficient and time-consuming. Even before cognitive symptoms show, AI systems may detect small changes in brain structure and function that are suggestive of Alzheimer's disease.

To remedy this deficiency, we used machine learning techniques and hospital data to build a disease prediction system using Python and the Tkinter interface. We were able to properly forecast the severity of a patient's condition by combining pre-existing data in the system with patient-reported symptoms. Before the user enters the symptoms, the system sends the characteristics and data to the prediction model, which also performs data pre-processing for future reference. Following that, various algorithms and techniques like Naive Bayes, Decision Tree, and KNN are used to classify the data.

By providing patients with easy and affordable options, the application of machine learning in disease prediction has the ability to disrupt the healthcare sector. We can construct a more robust and effective healthcare system for the future by integrating the most recent technological advances with the experience of healthcare professionals.

2 Literature Review

Classification of diseases was done from the radiology reports by Shipra Khedikar and Uma Yadav in their research paper [1]. The proposed methodology included picture enhancing techniques for pre-processing, image segmentation using the k-means algorithm, and grayscale and texture feature extraction from segmented images. Finally, SVM was used to categorize images. The authors identified why it would be difficult to use Artificial Neural Network (ANN) even though it provides greater accuracy and performance. This was because ANN carries very high costs of using electronic hardware and use of physical memory, which would be of great problem in the long run, considering the modus operandi that is followed in the healthcare sector in countries like India. The work in this paper showed a 96.77% accuracy in detecting the region of interest by highlighting the features. However, the drawback of this research work was that they only fed Computed Tomography (CT) Scan images to the model, rather than testing it out with other radiology reports to obtain the medical imaging of MRIs, ultrasound images, etc. This reduces the scope of the research work drastically. However, larger dataset with different kinds of images might have been fed into the model to boost accuracy and accomplish the project's goal of determining multiple diseases.

Dr. Babu Anto P. and Reema Mathew A. (2017) [2] proposed a method for identifying and classifying tumors. Anisotropic diffusion filters were used to analyze the MRI brain images in this investigation. Then, features were extracted using a discrete wavelet transform. SVM was then used to classify, following feature extraction, resulting in ultimately finding tumors. The suggested method's classification accuracy is 86%.

Krisna Nuresa Qodri et al. [3] investigated various approaches for detecting brain tumors in MRI images. They highlighted the point where CNN has been a very effective classifier with high accuracy which is also capable of handling a considerable amount of bias. On the other hand, they also discussed how the Support Vector Machine, Continuous Wavelet Transform, and Discrete Wavelet Transform all have computational flaws but still yield reliable results. Moreover, models like NASNetLarge that performed poorly during training and validation were found. Due to extremely large data losses in this model, which greatly reduced accuracy, the training as well as validation accuracy achieved by this model was 62%.

Mohd Fauzi Othman et. al. (2011) [4] detected brain tumors using the PNN classification approach. The proposed method trained a PNN classifier on twenty MRI brain images, yielding accuracy ranging from 73% to 100% depending on the smoothing factor for spread values.

Anil Parajuli (2016) [5] implemented the Naïve Bayes Classifier for prediction of diseases. The Nave Bayes Classifier assessed the probability of the incidence of diseases such as the common cold, malaria, and typhoid using basic symptoms specified in a check box form by the user. Author depicted great statistical skills by explaining her choice of Naïve Bayes as her classifier and how it would calculate the probability of occurrence of a particular disease. Author also implemented research work with great accuracy, but there still were a few limitations in her project. The Disease Predictor only calculated the probability of a person being sick because of a specific disease, which did not prove to be of any qualitative value. The user of this predictor would still have to visit a doctor for exact diagnosis and get the necessary medications prescribed by the doctor for the disease. There were also no signs of past history being considered for each user.

Kareem et al. (2023) [6] identified the size and variety of molecular structures in brain tumors as a challenge associated with MRI brain tumor detection. To identify brain malignancies in MRI data, they used deep learning approaches, including artificial neural networks, Naïve Bayes, and multi-layer perceptron. Also, they used effective pre-processing approaches to remove textural information from the brain MRI images. These results turned out to be very beneficial for us to train our own model.

The best medical diagnostic mining strategy was examined by K.M. Al-Aidaroos et al. [7]. The authors compared Naive Bayes against Logistic Regression, Neural Network, KStar, a simple rule-based technique (ZeroR), and Decision Tree. 15 actual medical instances were chosen to assess the efficacy of all treatments. The study found that Naive Bayes outperforms the remaining algorithms in 8 of 15 data sets, with the best accuracy for dermatological issues being 97.43% (ZeroR was the weakest here with 30.6% accuracy) and the lowest accuracy for Primary Tumor being 49.71%. However, the test results implied that the prediction accuracy outcomes in Naïve Bayes surpasses all the other models that were selected with an average accuracy of 60%. This proved to be an important foundation for our research as well.

Ekaterini S. Goudouris [8] offered a non-systematic evaluation of the COVID-19 laboratory diagnosis, which assisted us in identifying the major pain points to consider when determining the presence of the coronavirus. The author also introduced different types of tests which could help in determining the virus, however real-time polymerase chain reaction (RT-PCR) testing is declared to be the ideal standard of testing.

S. K. Chandra et. al. [9] addressed concerns with the identification of benign brain tumors. In the inchoate stages of brain tumor identification, segmentation is used. The authors recognized the limitations of existing segmentation algorithms, such as the difficulties in dealing with noisy data and identifying minor intensity variations in images. As part of their research, they developed a new fractional mask design to recognize benign brain tumors. Qualitative and quantitative analyses were also carried out to demonstrate superiority over previous boundary-based approaches.

Gurbina, Mircea et al. [10] used support vector machines and several wavelet transformations to achieve the identification and classification of MRI brain cancers. Their suggested approach attempted to segregate between healthy brain and malignant brain. Brain tumors are classified into two types: benign or low-grade and malignant or high-grade. Brain MRI was used to understand many forms of brain malignancies, including glioblastoma, sarcoma, and metastatic bronchogenic carcinoma tumors.

M Vamshi Krishna Reddy et. al. [11] highlighted the challenges in the traditional diagnosis process and how machine learning models such as decision trees, random forests, SVM, and logistic regression can assist in making accurate predictions of diseases based on symptoms. According to the authors, the random forest algorithm achieved the highest accuracy of 87.2%, followed by the decision tree algorithm at 83.2%. The authors discussed the proposed system's shortcomings and suggested that future research should focus on increasing the dataset and researching additional machine learning techniques to increase disease prediction accuracy.

3. Proposed Work

3.1 Tools and Platform Used

This project involved the development of a machine learning model that was then deployed as a web application. To achieve this, the project utilized a range of different tools and technologies, including several popular frameworks and libraries.

NumPy, which is well-known for having support for complex arrays and matrices, was one of the essential libraries used in this project. NumPy also includes a plethora of routines for working with these arrays. Another library used was Pandas, which is specifically designed for data manipulation and analysis.

For the backend of the web application, the project utilized Flask. Flask contains a debugger and development server, as well as built-in support for unit testing, RESTful request dispatching, and Jinja templating. This makes it an excellent choice for developing the web application's backend.

To provide additional functionality and support for the web application, the project also utilized Google Firebase. Firebase provides a variety of services that may be used to create high-quality mobile and online applications, such as real-time databases, authentication, and cloud storage.

The project uses many prominent machine learning libraries and frameworks to develop the CNN model for the web application.

Scikit-learn was used to implement a variety of classification, regression, and clustering techniques, including SVM and random forest.

OpenCV was also used to provide support for computer vision tasks.

TensorFlow was chosen as the primary framework for training text classification models for the web application. Finally, Keras was employed as a fundamental component of the closely knit TensorFlow 2 ecosystem.

Other tools and technologies utilized in the project included VS-Code as an IDE, Google Colab for model training, and GitHub for version control.

3.2 Dataset Used

i. Disease Detection based on Symptoms Model

The study conducted at New York-Presbyterian Hospital in 2004 and based on data from a University of Columbia investigation was used in this research. The first column of the data set presents the name of the disease, while the second column describes its symptom. The study focused on the 150 most common diseases and identified the most robust associations among them, grouping symptoms by the strength of the associations. To classify diseases and symptoms, the researchers used the MedLEE natural language processing system, which generated UMLS codes. Statistical techniques based on frequency and co-occurrence were then employed to analyze these codes.

ii. Disease Detection using MRIs/Scans

Data is collected from several different sources, like, IEEE GitHub repository, UCSD GitHub repository, Kaggle Datasets, etc.

3.3 Image Processing

A function is developed that may accept symptoms as input and generate disease predictions. The training dataset was prepared by assigning paths, establishing categories (labels), scaling images, clipping areas of interest from images, dividing the dataset into train, test, and validation sets, shuffling training examples, and normalizing the images. In a few instances, Data

Augmentation was also undertaken as shown in Fig 3.3.1.

Image sizes used for training the models are as follows:

- COVID-19 Detection Model: (224,224)
- Brain Tumor Detection Model: (224,224)
- Pneumonia Detection Model: (150,150)
- Alzheimer Detection Model: (176,176)

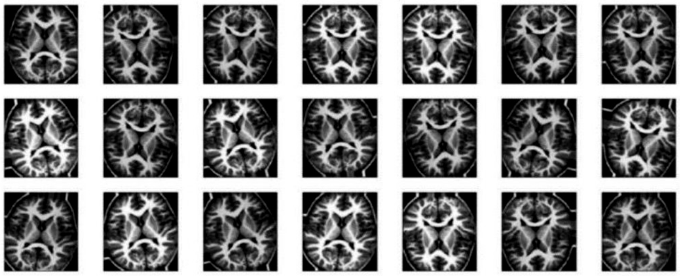

Fig 3.3.1. Augmented Image Dataset

Parameters for preprocessing using Image Data Generator class in TensorFlow are as follows

- rotation_range = 15,
- width shift range = 0.1,
- height_shift_range = 0.1,
- zoom_range = 0.2,
- shear_range = 0.1,
- brightness range = [0.5,1.5],
- color_mode = 'rgb',
- horizontal_flip = True,
- vertical_flip = True

A few additional measures are taken for data preprocessing in brain tumor identification to increase the model's performance. Extreme points in contours are found using Open CV to crop the brain out of the MRI as depicted in Fig.3.3.2.

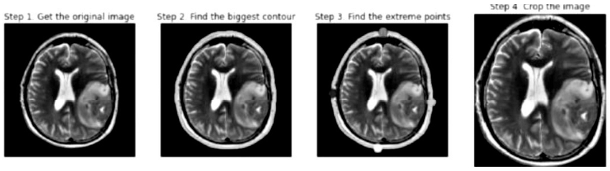

Fig 3.3.2. Finding Extreme Points using OpenCV

3.4 Models and Algorithms

In the realm of disease diagnosis, machine learning algorithms such as Naive Bayes Decision Trees, KNN, Random Forest, and have demonstrated promising results in accurately predicting illness outcomes based on symptoms. Despite these advances, studies have indicated that a considerable portion of the population continues to overlook small symptoms, potentially leading to more serious health problems in the future. To address this problem, machine learning algorithms are employed in the application to detect and prevent diseases in their earliest stages.

Attempts to employ machine learning for early disease detection and prevention continue to increase and improve as society strives to enhance human well-being in a competitive global economy.

The four machine learning techniques employed to provide a comprehensive perspective of the data and more reliable predictions from the patient's symptoms are–

- Decision Tree
- Random Forest
- KNN
- Naive Bayes

a. Decision Trees

Decision Trees, as shown in Fig. 3.4.1, divide a dataset into subsets depending on the most significant features until a stopping criteria is met, such as obtaining a maximum tree depth or a minimum number of samples in a leaf node. The generated tree can then be utilized to predict the target variable for future instances. In addition to their interpretability, versatility, and ability to handle both categorical and numeric data, they offer a number of benefits. Moreover, Decision Trees can manage missing values and outliers.

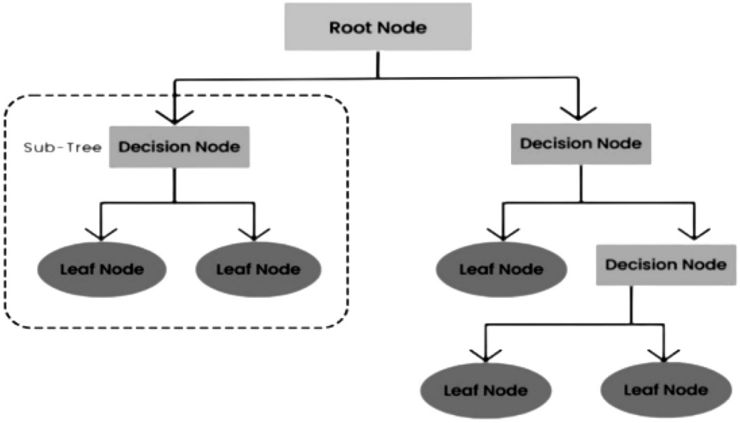

Fig 3.4.1. Decision Trees Flow Diagram

b. Random Forest

Random Forest as depicted in Fig. 3.4.2 uses the supervised learning approach. It is based on ensemble learning, a technique for tackling tough problems by combining numerous classifiers and enhancing the model's performance.

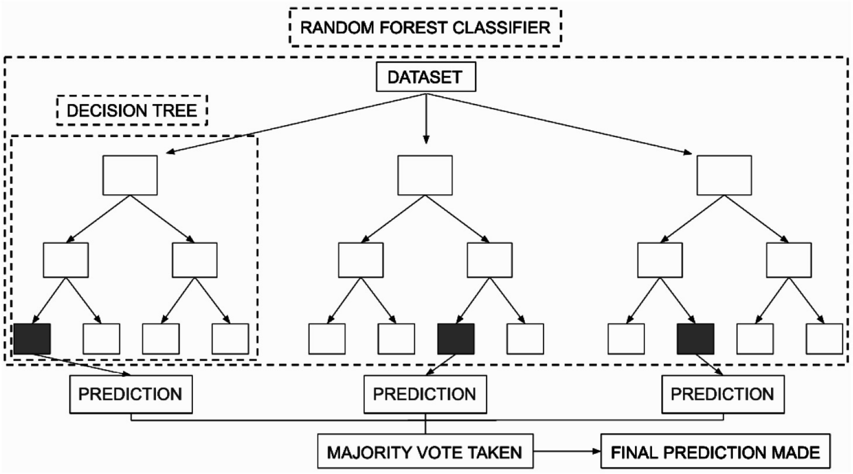

Fig 3.4.2. Random Forest Flow Diagram

c. K-Nearest Neighbors (KNN)

KNN is a machine learning algorithm used for classification and perform regression. It uses a distance metric (e.g., Euclidean distance) to find the K nearest data points to a new input point in the training set and then making a prediction using the most common class label or average target value of these K neighbors, as shown in Fig. 3.4.3. KNN is capable of capturing non-linear correlations between input characteristics and target variables and performs well even when the training data is noisy or contains insignificant data.

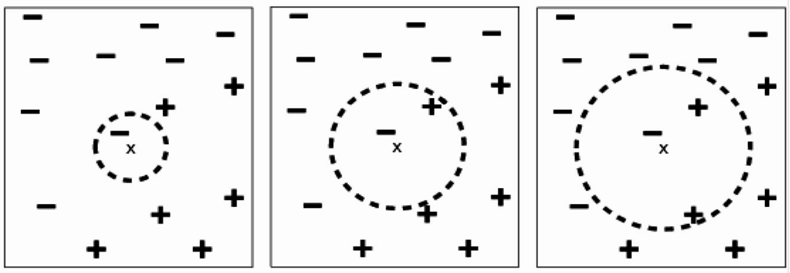

Fig 3.4.3. KNN Flow Diagram

d. Naïve Bayes

The Naive Bayes classifier includes employs the Bayes method for prediction. There are several algorithms that necessitate more processing power than this. As a result, it can be utilized to rapidly make mining models to find connections between input and anticipated columns. In the development of classifiers, the Naive Bayes approach is most widely used. To anticipate categorical class labels, certain classifiers are utilized. Identification of classes is done using classifiers by bucketing them into specific classes.

In healthcare, medical image analysis plays a critical role in accurate diagnosis, early detection, personalized treatment, efficiency, and remote diagnosis. Analyzing medical images using technology, such as machine learning and computer vision algorithms, can assist in identifying minute patterns and irregularities that the human eye may find difficult to discern, enabling healthcare professionals to diagnose diseases and conditions accurately. Automated analysis of medical images can save time and resources, allowing healthcare professionals to diagnose and treat more patients. Additionally, analyzing medical images using technology can facilitate remote diagnosis, allowing healthcare professionals to provide care to patients in remote areas or in emergencies.

The following technology is used to conduct analysis on MRIs, X-Rays, CT Scans, etc. and identify the particular diseases -

a. Convolutional Neural Network (ConvNet/CNN)

A CNN may take an image as input and apply weights and biases, which help in prioritizing and identifying distinct aspects/objects in the image. It is shown in Fig.

3.4.4. ConvNet requires considerably less preprocessing than other classification algorithms. While basic techniques necessitate the creation of filters by hand, ConvNets are powerful computational systems that can learn these filters with enough practice. The Visual Cortex layout inspired the creation of a ConvNet, which is analogous to the network of connections in the human brain [24].

A ConvNet successfully captures the Spatial and Temporal correlations in a picture by utilizing the suitable filters. The aim of ConvNet is to compress the images into a more manageable format while keeping the critical features for efficient forecasting. ConvNet's major goal is to keep vital attributes.

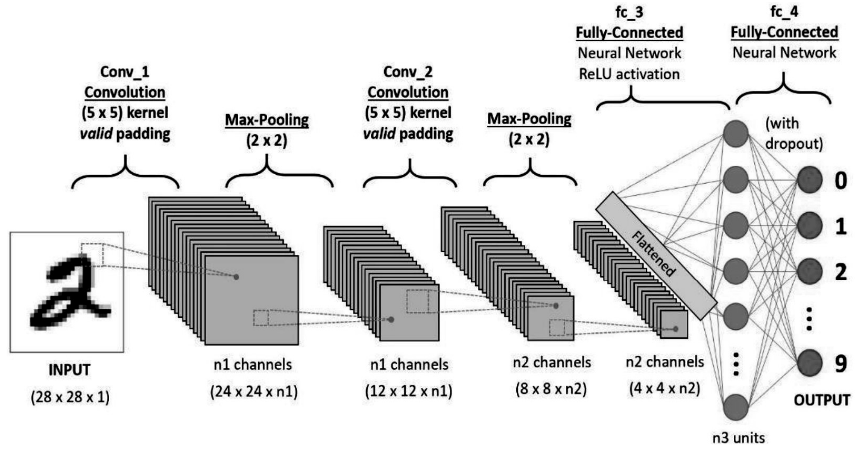

Fig 3.4.4. CNN Architecture

3.5 Methodology

A web application has been created that uses various algorithms for the 2-stage disease detection model as per proposed solution. These algorithms include:

- Usage of a combination of Gaussian NB, SVC and Random Forest Classifier to create a high accuracy model for detection of various diseases using symptoms as shown in Fig. 3.5.1, Fig. 3.5.2, and Fig. 3.5.3 respectively.
- Logistic Regression and Decision Tree Classifier to create a moderate level model for detecting COVID-19 using various symptoms.
- For the second stage X-ray scans and MRIs are used to predict Brain Tumor, Pneumonia, Alzheimer's and COVID-19 using CNN as in Fig. 3.5.4.

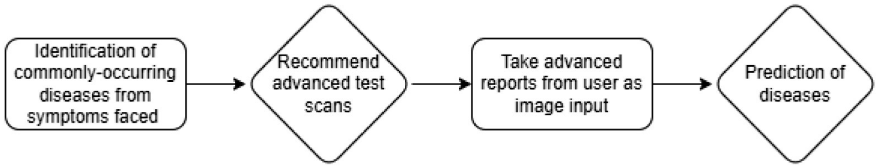

Fig 3.5.1. Overall Model Architecture

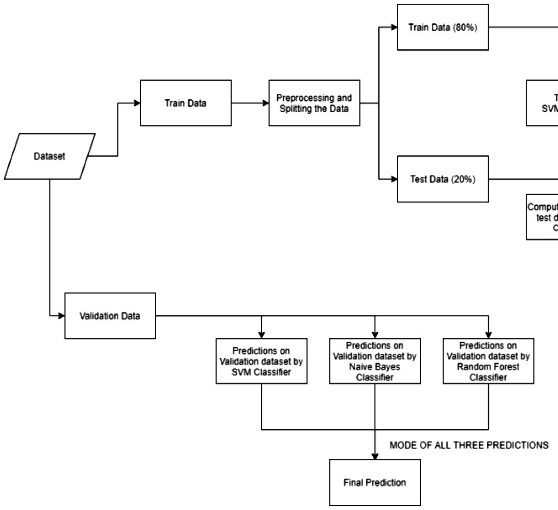

Fig 3.5.2. Model Architecture for Disease Prediction using Symptoms

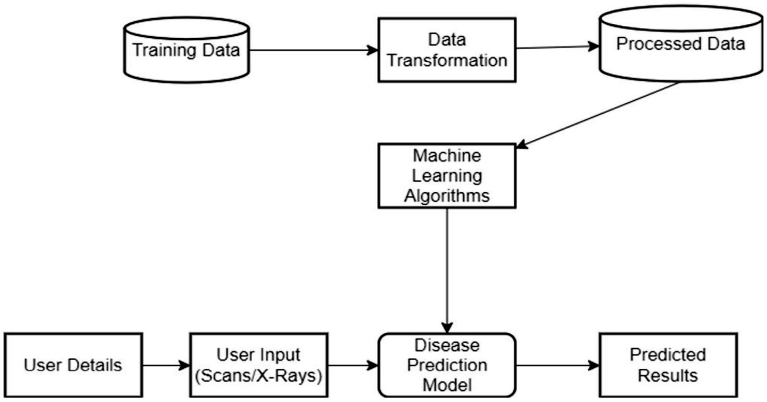

Fig 3.5.3. Model Architecture for Disease Prediction using Image Data

Stage I - In this stage, the aim was to create a comprehensive dataset that would enable us to perform the necessary operations to draw accurate conclusions. Following data preprocessing, which involved removing null values, dropping irrelevant columns, and label encoding, we obtained a cleaned dataset comprising 132 parameters. This dataset was utilized to develop a model capable of identifying commonly occurring diseases based on the symptoms felt by the user. Our model operates in two stages, where in the first stage, it filters out unlikely diseases based on basic symptoms reported by the patient. On this dataset, we used K-Fold Cross-Validation and used Random Forest Classifier, Gaussian NB, and SVC as our model. An interactive chatbot is deployed that can take real-time symptoms as input and generate predictions for disease.

Stage II – After filtering the diseases, the user is recommended a few advanced tests that he/she should take to diagnose the exact disease and start the treatment for the same immediately. The test could be as simple as an X-Ray to further complex tests like MRI Scans and CT scans. The user would then input the test results in the form of image/text which would help identify whether the patient has Alzheimer's disease or a Brain Tumor. We have predicted the disease based on the image/text they feed to the system using a Convolutional Neural Network (CNN) as shown in Fig.3.5.5 and Fig. 3.5.6 respectively. By engaging a convolutional layer of 3x3 filter with a stride 1 working in conjunction with max pool layer of 2x2 filter with stride 2 the number of hyperparameters has been efficiently reduced. For Brain Tumor, the following configuration in the VGG16 model was done as in Fig. 3.5.7.

- 16 weighted layers make up VGG16. In total, VGG16 has 21 layers consisting of 13 convolutional layers, 4 max-pooling layers, 3 dense layers, and 5 max pooling layers. VGG16 takes input tensors of size 224, and 244 with three RGB channels each.
- Three RGB channels and 224,244 pixels are the input tensor size for VGG16.
- Filters are divided among four layers: Conv-1, 2, 3, 4 with 64,128,256 and 512 filters respectively.
- Following these, there are three Fully Connected layers (FCs). In the third of these, there are 1000 channels and 1000-way ILSVRC classification is performed. First and second FC layers each contain 4096 channels.

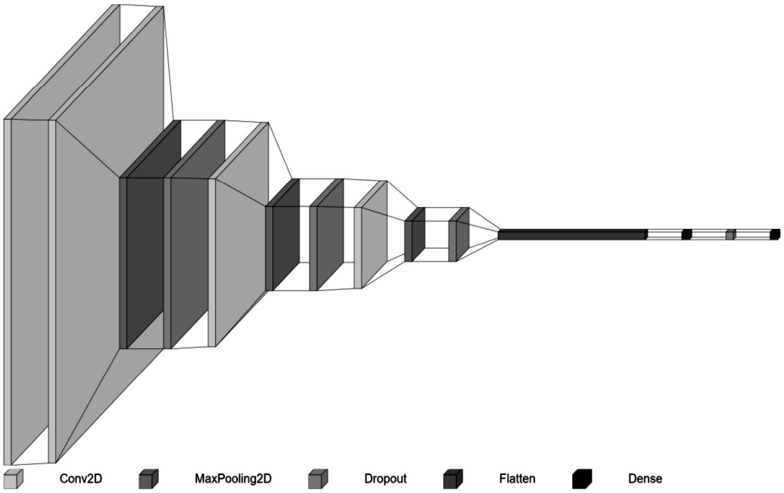

Fig 3.5.4. Sequential CNN Model for COVID-19

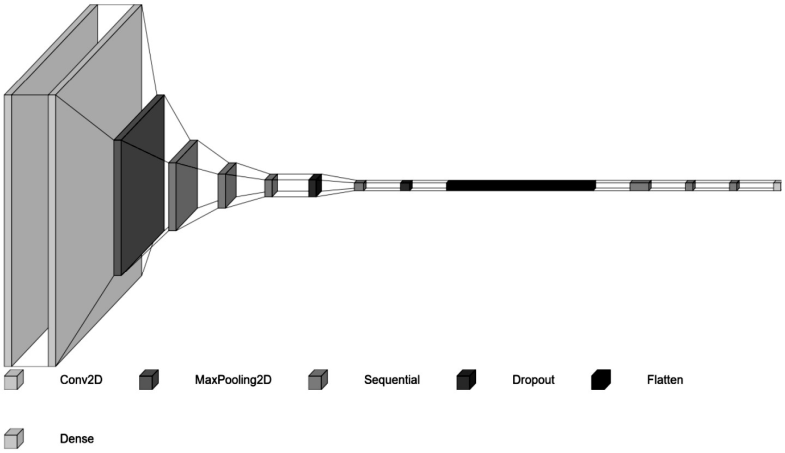

Fig 3.5.5. Sequential CNN Model for Alzheimer's Disease

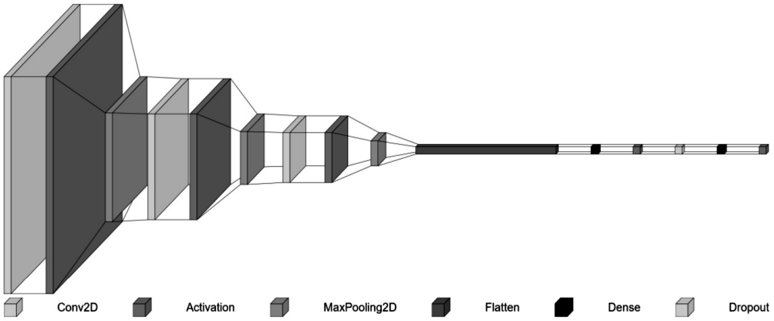

Fig 3.5.6. Sequential CNN Model for Pneumonia Disease

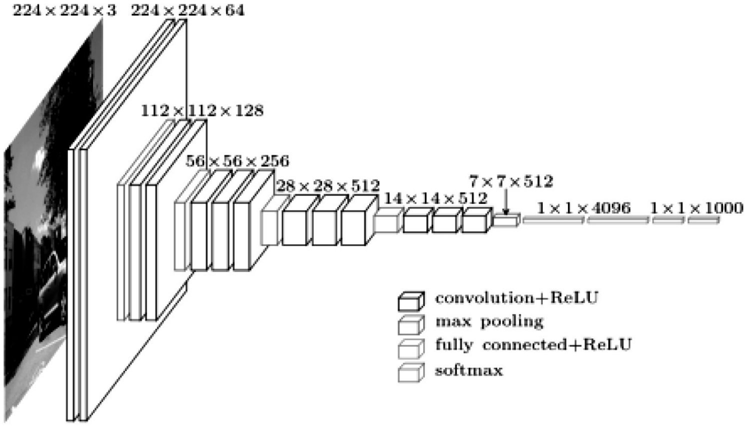

Fig 3.5.7. CNN Model with Transfer Learning using VGG16 for Brain Tumor

4. Results and Discussion

We have had great success with the accuracy of our models for most diseases. They are plotted in Fig. 4.1, Fig. 4.2, Fig. 4.3, and Fig. 4.4 respectively. For brain tumor detection, more data points can be explored as a future scope to achieve higher accuracy. The Alzheimer's detection model did not fare since there were four classes in the dataset, a more complex architecture is needed to train this model, or weights can be used from a pre-trained model as done in the case of brain tumor detection. VGG16 was used as the base model for transfer learning in brain tumor detection.

Table. 4.1. Accuracy of the Proposed Model

Stage 1			
Sr. No.	Type of Disease	Model Used	Accuracy
1	Commonly occurring diseases	Combination of Decision Tree, Random Forest, KNN, Naive Bayes	94.88%
Stage 2			
Sr. No	Type of Disease	Model Used	Accuracy
1	Alzheimer's Disease	CNN	73.54%
2	Brain Tumor	CNN	97.38%
3	COVID-19	CNN with pre-trained VGG 16 weights	93%
4	Pneumonia	CNN	83.17%

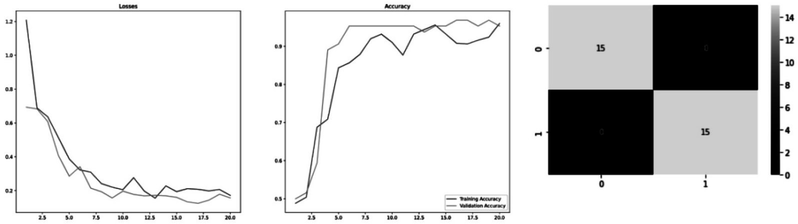

Fig 4.1. Loss-Accuracy Plot & Confusion Matrix of the COVID-19 detection model

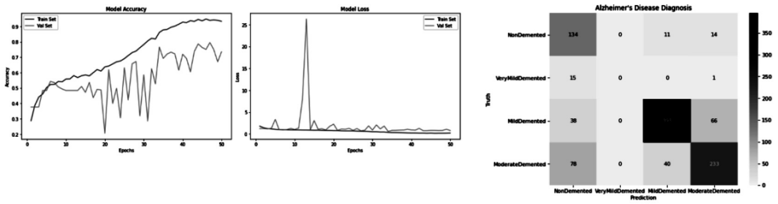

Fig 4.2. Loss-Accuracy Plot & Confusion Matrix of the Alzheimer's detection model

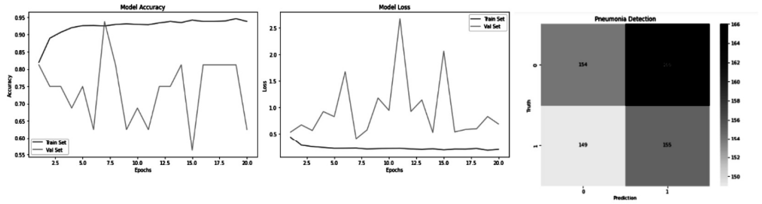

Fig 4.3. Loss-Accuracy Plot & Confusion Matrix of the Pneumonia detection model

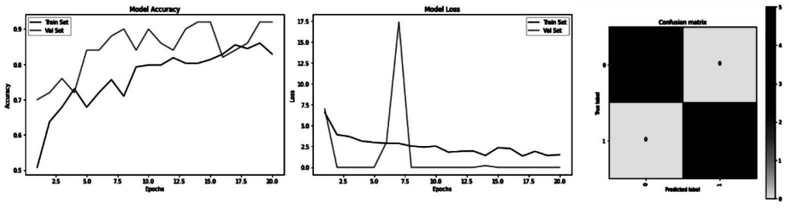

Fig 4.4. Loss-Accuracy Plot & Confusion Matrix of the Brain Tumor detection model

5. Conclusion

Traditional machine learning methods such as SVMs and multilayer perceptron machines have limitations when used to challenging classification tasks with strong semantic information. These models are often based on shallow structures, meaning they have a limited number of samples and computing units, which limits their ability to capture complex relationships between features in the data.

Convolutional neural networks (CNNs), on the other hand, have emerged as effective deep learning models capable of dealing with complicated classification issues, particularly in the field of image processing. CNNs perform at the cutting edge on many benchmarks when it comes to picture classification and identification tasks.

CNNs use a feature detection layer to learn implicitly from training data, allowing them to identify translation, scaling, and other types of distortion-invariant images. This layer detects features that are relevant to the image classification task and then use these features to create a higher-level representation of the input image. The weights of this layer are learned through backpropagation, allowing the network to adjust them to improve the accuracy of its predictions.

This weight sharing also enables CNNs to learn features that are insensitive to certain transformations, such as scaling and translation.

CNNs can handle multidimensional input vector pictures successfully, reducing the complexity of data reconstruction from feature extraction and image classification techniques. This is accomplished by parallel processing, making CNN extremely efficient and accurate for visual feature representation and classification.

According to the findings of our studies, there is a huge difficulty with communication among physicians in India. Our team has devised a solution to this challenge that aims to offer professionals a comprehensive view of their patient's medical history and current pharmacological regimen.

We think that by doing so, we will construct a more consistent and compelling image on which clinicians can make their judgments.

Our suggested method entails developing a centralized database including all pertinent medical information for each patient. All clinicians involved in the patient's treatment will have access to this database, enabling smooth communication and collaboration among medical experts. Doctors will be able to make better-educated judgments regarding their patients' treatment plans if they have a 360-degree perspective of their medical history and current pharmaceutical routine.

Furthermore, this system will aid in the reduction of medical errors and the overall quality of care provided to patients.

Doctors will be able to recognize any concerns or complications that may occur and take the appropriate actions to prevent them if they have a thorough awareness of a patient's medical history.

6. References

1. Khedikar, Shipra, and Uma Yadav. "Identification of Disease by Using SVM Classifier." International Journal of Advanced Research in Computer Science and Software Engineering 7.04 (2017).
2. Mathew, A & Anto, Babu. (2017). Tumor detection and classification of MRI brain image using wavelet transform and SVM. 75-78. 10.1109/CSPC.2017.8305810.
3. Qodri, Krisna Nuresa, Indah Soesanti, and Hanung Adi Nugroho. "Image Analysis for MRI-Based Brain Tumor Classification Using Deep Learning." IJITEE (International Journal of Information Technology and Electrical Engineering) 5.1: 21-28.
4. Othman, Mohd Fauzi, and Mohd Ariffanan Mohd Basri. "Probabilistic neural network for brain tumor classification." 2011 Second International Conference on Intelligent Systems, Modelling and Simulation. IEEE, 2011.

5. Parajuli, Anil. DISEASE PREDICTOR. Diss. Ph. D. diss., Tribhuvan University, 2016.
6. Kareem, Shahab & Abdulrahman, Bikhtiyar & Hawezi, Roojwan & Khoshaba, Farah & Askar, Shavan & Muheden, Karwan & Abdulkhaleq, Ibrahim. (2023). Comparative evaluation for detection of brain tumor using machine learning algorithms. 10.11591/ijai.v12.i1.pp469-477.
7. K. M. Al-Aidaroos, A. A. Bakar and Z. Othman, "Naïve bayes variants in classification learning," 2010 International Conference on Information Retrieval & Knowledge Management (CAMP), 2010, pp. 276-281, doi: 10.1109/INFRKM.2010.5466902.
8. Goudouris ES. Laboratory diagnosis of COVID-19. J Pediatr (Rio J). 2021;97:7–12.
9. Chandra, Saroj Kumar and Manish Kumar Bajpai. "EFFECTIVE ALGORITHM FOR BENIGN BRAIN TUMOR DETECTION USING FRACTIONAL CALCULUS." TENCON 2018 - 2018 IEEE Region 10 Conference (2018): 2408-2413.
10. Gurbina, Mircea et al. "Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines." 2019 42nd International Conference on Telecommunications and Signal Processing (TSP) (2019): 505-508.
11. M Vamshi Krishna Reddy, G V P Sai Abhijith, K Sai Nath, Mangali Sathyanarayana."Disease Predictor Based on Symptoms Using Machine Learning", Volume 10, Issue VI, International Journal for Research in Applied Science and Engineering Technology (IJRASET) Page No: 2549-2555, ISSN : 2321-9653, doi - 10.22214/ijraset.2022.44408
12. Surendra Patro et al 2022 IOP Conf. Ser.: Earth Environ. Sci. 1032 012045, doi - 10.1088/1755-1315/1032/1/012045
13. Yan Y, Yao X-J, Wang S-H, Zhang Y-D. A Survey of

Computer-Aided Tumor Diagnosis Based on Convolutional Neural Network. Biology. 2021; 10(11):1084. https://doi.org/10.3390/biology10111084

14. S. Ghulyani, D. Jain, P. Singh, S. Joshi and A. Ahlawat, "A Data Entry Optical Character Recognition Tool using Convolutional Neural Networks," 2022 IEEE IAS Global Conference on Emerging Technologies (GlobConET), Arad, Romania, 2022, pp. 721-728, doi: 10.1109/GlobConET53749.2022.9872395.
15. Kaveh Nasiri, Aleksandra Dimitrova, Comparing saliva and nasopharyngeal swab specimens in the detection of COVID-19: A systematic review and meta-analysis, Journal of Dental Sciences, Volume 16, Issue 3, 2021, Pages 799-805, ISSN 1991-7902, https://doi.org/10.1016/j.jds.2021.01.010.
16. A. Castiglione, M. Umer, S. Sadiq, M. S. Obaidat and P. Vijayakumar, "The Role of Internet of Things to Control the Outbreak of COVID-19 Pandemic," in IEEE Internet of Things Journal, vol. 8, no. 21, pp. 16072-16082, 1 Nov.1, 2021, doi: 10.1109/JIOT.2021.3070306.
17. P. Ouppaphan, "Corn Disease Identification from Leaf Images Using Convolutional Neural Networks," 2017 21st International Computer Science and Engineering Conference (ICSEC), Bangkok, Thailand, 2017, pp. 1-5, doi: 10.1109/ICSEC.2017.8443919.
18. Amirhossein Ahmadieh-Yazdi, Ali Mahdavinezhad, Leili Tapak et al. Identifying metastatic biomarkers of colorectal cancer: Machine learning modeling and experimental validation, 13 March 2023, PREPRINT (Version 1) available at Research Square [https://doi.org/10.21203/rs.3.rs-2618089/v1]
19. S. K. Chandra and M. Kumar Bajpai, "EFFECTIVE ALGORITHM FOR BENIGN BRAIN TUMOR DETECTION

USING FRACTIONAL CALCULUS," TENCON 2018 - 2018 IEEE Region 10 Conference, Jeju, Korea (South), 2018, pp. 2408-2413, doi: 10.1109/TENCON.2018.8650163.

20. A. Gokarn, K. Patni, Y. Purohit and R. Sonkusare, "COVID-19 Radiography Using ConvNets," 2022 4th International Conference on Control Systems, Mathematical Modeling, Automation and Energy Efficiency (SUMMA), Lipetsk, Russian Federation, 2022, pp. 407-411, doi: 10.1109/SUMMA57301.2022.9973882.
21. K.M. Al-Aidaroos, A.A. Bakar and Z. Othman, 2012. Medical Data Classification with Naive Bayes Approach. Information Technology Journal, 11: 1166-1174. DOI: 10.3923/itj.2012.1166.1174
22. Irshad Ullah, "Data Mining Algorithms And Medical Sciences",IJCSIT, Vol 2, No 6, December 2010
23. Amit Kumar Das, Aman Kedia,"Data mining techniques in Indian Healthcare: A Short Review", 2015 International Conference on Man and Machine Interfacing (MAMI), 978-1-5090-0225-2/15
24. M. Saranya, N. Archana, J. Reshma, S. Sangeetha and M. Varalakshmi, "OBJECT DETECTION AND LANE CHANGING FOR SELF DRIVING CAR USING CNN," 2022 International Conference on Communication, Computing and Internet of Things (IC3IoT), Chennai, India, 2022, pp. 1-7, doi: 10.1109/IC3IOT53935.2022.9767882.