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A Novel Approach towards Healthcare using Identity Access Management and Machine Learning

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Abstract: Advances around the field of deep learning and cognitive computing have allowed mankind to look at and solve the problems of the world in a completely new way. Early detection of some deadly diseases helps save millions of lives but still, it has been observed that there seems to be no change in the way diagnosis of a particular disease takes place even in the 21st Generation of Medical Health Care. The highlight of the reasons happens to be Lack of Trust, Lack of Awareness, and Lack of Infrastructure. The health care industry seems to land blocked by their rigid methodologies and to this date, there is no involvement of the patient and caretaker staff in the digitalization of healthcare. In this project, we will introduce a digital platform for healthcare that aims to reduce the gap between a doctor, patient, and the caretaker staff. This platform is based on data, that can assist surgeons, patients, and care teams throughout the patient journey by automating some of the critical processes that are now done manually, including decision-making, post-surgery planning, tracking, and estimating recovery time, smart disease detection models, and collecting patient feedback. An important aspect of this platform will be the disease prediction models wherein we have prepared three different disease prediction models that will be able to detect if a user has that specific disease or not without the consultation of the Doctor. Here we have talked about the adoption of Deep Learning and Artificial Intelligence in today's Healthcare scenario and the crucial role of delivering such applications to the user on a single platform.

Keywords: Identity Access Management, Medical Image analysis, Convolution neural network, Disease detection algorithms, ResNet-101, ResNet-50, Mask RCNN, Deep learning models.

I. INTRODUCTION

Nowadays, everyone has a smart gadget that links them to the internet, and here is where the speed of data transfer or data availability comes into play. Many people who want medical services for minor inconveniences but are unable to travel for required medical treatment might benefit from this digital method. Medical image analysis is one of those fields which have seen some breakthrough research and provides applications such that will benefit millions of people. An important aspect to focus on Medical image analysis is the algorithm on which it is based upon. Machine learning (ML) algorithms can be defined as programs that understand the complexity of the task they are designed for and are able to perform better as and when they are exposed to more and more data. Such machine learning algorithms were first introduced in 1960 by Arthur Samuel. These algorithms are designed employing the logics of statistics and mathematics which make the deep learning model accurate and functional. To build such accurate disease models it is desirable that these models work on well-designed neural networks. A disease prediction model's building blocks are neural networks. They are used in a variety of financial services applications, ranging from forecasting and market research to fraud detection and risk assessment. The fundamental benefit of a neural network is that it adds computational capabilities to the model, reducing the need for human interaction in the model's operation [1].

II. LITERATURE SURVEY

Automated disease detection in medical imaging is turning out to be an emerging field in the different sectors of medical diagnostic applications. The idea of image classification using ML can help detect some specific disease at an early stage, even diseases as crucial as brain tumour, pancreatic tumour, covid-19 etc. Automated disease identification and diagnosis in advanced medical scans and imagery is critical because it gives information about aberrant tissues that is required for treatment planning. Human examination is the most common approach for detecting defects in Magnetic Resonance Image (MRI) brain images.

We may also remark that this approach may be impractical when dealing with big volumes of data. As a result, automated disease identification and diagnosis detection systems are being developed in order to save radiologists time.

In the realm of medical image analysis, innovations in the areas of artificial intelligence techniques for the classification, segmentation, and grading of different malignancies using various imaging modalities have lately grown more prominent. Database operations such as feature extraction and data augmentation are a few methods related to data pre-processing that aim to classify, filter and clean the dataset for better operations. In order to carry out the comparative study, the research has been carried out on a number of existing models that have been suggested and developed by various researchers over time. In order to segment brain tumours, one of the proposed models employs the convolution neural network (CNN) method and the fuzzy c-mean strategy. Their model had a 97% per cent sensitivity rate and a 96.97% accuracy rate. They extracted four distinct features which symbolize the different properties of each image, which in this case is an MRI scan of the brain, utilizing the four angles (0°, 45°, 90°, and 135°) using this method. Meningioma-glioma dataset (Mg-Gl), meningioma-pituitary tumour dataset (Mg-Pt), Glioma-Pituitary tumour dataset (Gl-Pt), Meningioma-glioma-pituitary tumour dataset (Gl-Pt), Meningioma-glioma-pituitary tumour dataset (Mg-Gl-Pt). The four datasets Mg-Gl, Mg-Pt, Gl-Pt and Mg-Gl-Pt were donated by China's school of biomedical engineering [2], [3]. A deep convolution neural network-based framework for brain tumour recognition and reviewing was introduced. The notion of fuzzy c-means (FCM) was used for brain division, and these sectioned areas and form highlights were eliminated before being fed into support vector machines and convolution neural network classifiers. The performance metrics projected that the framework was able to accomplish a value of 97.5% accuracy [4]. Later on, another system was proposed in which a strategy that uses the area of interest augmentation and fine ring-form partition to improve the efficiency of the brain tumour classification procedure. They utilized comparable feature extraction approaches, such as the bag-of-words (BoW), which involves feeding these feature vectors into a classifier. The accuracy of the and BoW and other feature extraction methods improved from 88.92% to 90.98%, respectively, according to the experimental findings. Another study used a novel approach of the convolution neural network for non-invasive segmenting and classifying glioma brain tumours. The categorization was completed using a complete scan of the MRI images of the brain therefore the picture marker was not at the pixel level, but rather at the image level. The final metrics obtained from the experiments revealed that this approach was successful with an inexpensive performance with an accuracy of 90.36% [5]. Sajjad, Muhammad, et al. [6] for brain tumour classification, researchers investigated a system that was used via various dataset operations for pre-processing approach with the CNN. The approach employed segmented MRI scans of the brain to classify brain cancers into many grades. For classification, they employed the pre-trained VGG-19 CNN architecture, which has an accuracy of 87.58% and 90.47% for data bedsore pre-processing and after pre-processing. While Özyurt, Fatih et al. [7] for brain tumour classification created a method, which combines CNN methods with neutrosophic and expert maximum fuzzy entropy. For brain tumour segmentation, they utilized the neuromorphic set and expert maximum fuzzy-sure entropy methods, and then these pictures were given to the CNN to extract features, and then to the SVM classifiers, which is a machine learning algorithm, for further categorization. They achieved a mean success of 94.68%. In this bibliographic review paper, we have gone through close to 34 research papers from the Scopus directory where we have inferred the following observations which will prove to be useful in our proposed system. According to a study published on the subject of fusion and extraction of features from a deep neural network, A strategy was proposed that uses fusion attribution to better describe pictures for face recognition using deep CNN attribute extraction. They utilized principal component analysis to decrease the fused attribute's capacity. For two classes, the SVM machine classifier is used. This method can detect faces with extreme occlusion, substantial confusion, and size discrepancies, according to test results. On the face detection dataset and benchmark, this approach achieves an 89% recall rate, according to the conclusion, and was also found to be 97% accurate [8]. Er-Yang Huan et al. [9], CNN-based body constitution' recognition system that can recognize individual constitution' types which is basically based on face scans. The suggested model first extracts the facial picture ascribed with CNN, then combines the preoccupied highlights with the tone credits. To obtain the gathering result, the combined subtleties are sent to the Soft-max classifier. They claim that such a method suggested during this research can achieve an accuracy of 65.3%. A new and innovative method had also been introduced in which a cycle of functions was designed using a fuzzy c-means collecting technique, conventional computations, and CNN, extract brain tumours from a 2-D MRI brain. The observational research was focused on a real-time dataset containing a variety of malignant growth measures, spots, patterns, and image quality. Six standard classifiers were used in the old-style calculation area, including SVM, k-nearest neighbours, multilayer perceptron, logistic regression, nave Bayes, and random forest, which were all used in scikit-learn. CNN received a 97% efficiency rating [10]. The research first explains the most often used processes in paragraph attribute extraction, then expands on the frequently used DL process in paragraph attribute extraction and its implementation, and anticipates the application of machine learning in feature abstraction. They conclude that associated with other machine learning approaches.

From nearly unprocessed original data, Deep Learning (DL) can detect complex interactions from the characteristic and train lower-level characteristics [11]. The research uses learning neural networks to classify brain cancers by Heba Mohsen et al. [12], they used a Deep Neural Network (DNN) to classify a batch of 66 MRI pictures of brain tumours. In terms of effectiveness, they find that the DNN approach beats conventional classifiers. A convolutional network is used for grouping and segmentation in an efficient and effective method. For abstract characteristics, the proposed method used ImageNet. For grouping and segmentation, the results were 97% and 84% precise, respectively [13]. DL structures and base neural frameworks for disease ordering by MRI pictures are thought of and assessed. The results reveal that the framework routine based on the neural network's specificity and sensitivity outperformed Artificial Neural Network (ANN) by 19% [14]. A new approach that uses CNN to classify brain tumours into benign and three types has been proposed. Using an enhanced independent component analysis composite model, the tumour is predominantly segmented from MRI images. Features are extracted and placed after the image has been segmented. This study looks at the statistical features of brain tumours including structure, texture, and signal intensity to see if they might predict treatment benefit like tumour existence and treatment response. Many conclusion studies have been conducted to investigate the role of CNNs in segmenting brain tumours by first conducting an enlightening look into CNNs and then doing dissertation research to obtain an example segmentation pipeline. Also, to look into the long-term efficacy of CNNs by looking into a new field called radionics. This research examines the quantitative characteristics of brain tumours such as form, texture, and signal intensity in order to predict clinical outcomes such as the presence of tumours and treatment response [15]. Research suggests that the detection of a brain tumour by applying CNN and ANN classification in a sequential way. To create a more detailed architecture, small kernels and neuron weight were devised. The CNN records 97% accuracy with minimum difficulty, according to research findings, and therefore the latest techniques [16]. After inferring from the confusion matrix and results from the algorithm the Network records 74% accuracy. Using a convolutional network within three kernels, the auto differentiate approach is used to identify cancer. The approach simultaneously accomplished the initial identification of the whole core and enhanced regions in dice likeness and quantity metrics by 0.85, 0.81, and 0.75, respectively [17]. Research conducted on the subject of DL and its role in covid-19 which aimed at diagnosing and detection of coronavirus-19 disease through various radiology modalities such as x-rays and Computed Tomography scans (CT scans). This model was able to provide was higher than 92% [18]. The CNN algorithm is used to extract target properties from sonar images during the research of a CNN algorithm. The SVM is used in the recognition step and was trained on data that was initially produced. The outcome illustrates the value of fully convolutional attribute extraction [19]. Applications of DL is a subject centred around how the actual applications of DL in medical are making a difference and saving millions of lives. It talked about different techniques such as medical imaging, History of medical imaging, CNN, supervised learning models and clustering [20]. At present a method for the CNN calculation and data augmentation and picture preparing to sort mind MRI filter pictures into threatening and non-dangerous. Examining the results of the scraping CNN computation using previously constructed VGG-16, ResNet 50, and Inception V3 models. In the end, the model's precision was 99.95 percent, while VGG-16's was 95%. ResNet 50 had an accuracy of 87%, while Inception-V3 had an accuracy of 78% [21].

III. PROPOSED SYSTEM

The major goal of this project is to create, implement, and build a system that provides assistance for hospital administration, which can only be accomplished by meeting the secondary goals that will be discussed next. One of the project's goals is to increase usage efficiency, which is assessed by the expressivity and consistency of the graphical user interface. When utilizing a system, a user is deemed efficient if the time required to complete a job reduces with each use. Another goal is to provide a system that enables for future enhancements and additions of present capability. The system should allow users to manage patient information, doctor information, schedule appointments, read prescriptions, and make payments online. The current system is not fully digital; most activities, including as patient registration, exchanging reports, and distributing prescriptions, are still done on paper and take a long time. This system has focused on lowering the quantity of paperwork involved in these processes as well as the time it takes to complete them. There is also a predictor module that can forecast a patient's illness.

IV. METHODOLOGY

The objective of developing a detection model using machine learning algorithms is to assist physicians in detecting and identifying diseases early on, which will benefit the treatment of health-related issues. A sample data for three diseases has been collected separately and developed for the sake of better accuracy and more optimized code quality. The three disease detection models include brain tumour detection, pancreatic tumour detection and covid-19 detection. All three models utilize different python libraries and ML algorithms, hence we created three different models.

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Upon the development of the three detection models, we constructed a software architecture to make these three disease detection models that were developed available to anyone on the internet via a hosted server. Every development of disease detection models requires a set of mandatory steps before applying the model training and testing. They are namely data extraction, data pre-processing and data normalization. In this section of the paper we will discuss the key aspects of the paper that are Identity Access Management (IAM) and ML. Machine Learning for healthcare technology consists of algorithms that use self-learning neural networks to improve treatment quality by assessing external data such as a patient's condition, X-rays, CT scans, and numerous tests and screenings. IAM in healthcare should focus on managing all forms of identities, including users, privileged users, patients, devices, and apps, as well as provisioning access to target systems and resources for sensitive data, such as Electronic Medical Records (EMR), using fine-grained access restrictions. IAM is a genuine strategy to ensuring healthcare data remains confidential. It manages access rights and establishes a password policy to give users secure access to medical documents, reports and other files in healthcare IT systems. Fig. 1 shows the user flowchart for the proposed smart healthcare management system after which we discuss the IAM and Disease Detection Models.

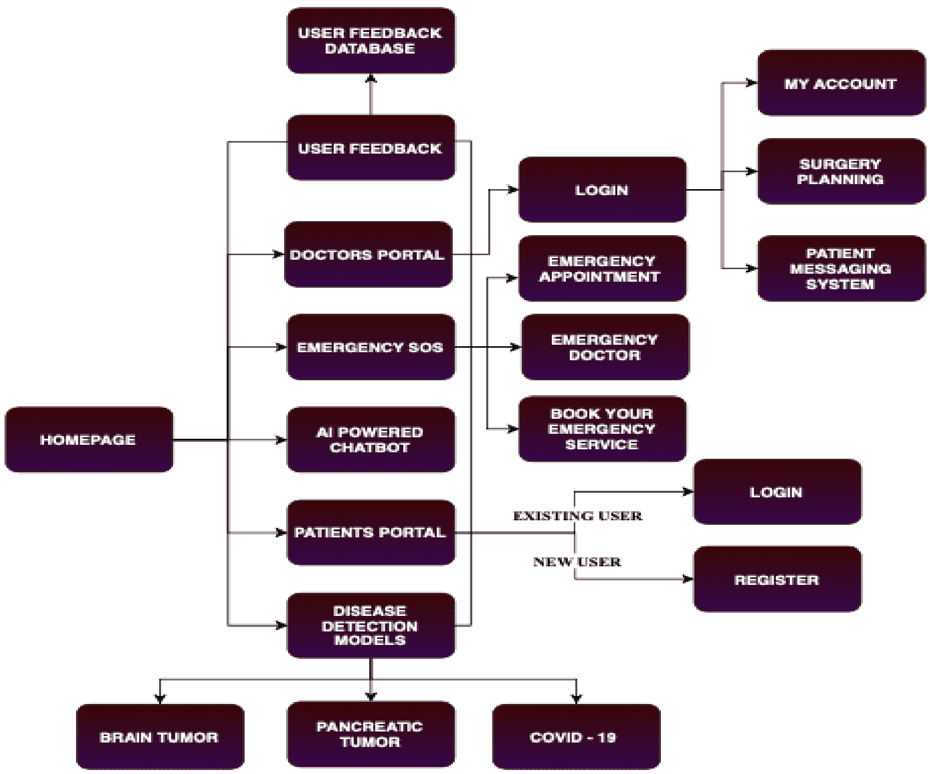

Fig. 1: Flowchart for Proposed Healthcare Management System

A. *Identity Access Management*

Identity and Access Management is a security discipline that allows the appropriate people to access the appropriate resources at the appropriate times for the appropriate reasons. IAM solves the mission-critical requirement for ensuring appropriate resource access in increasingly varied technological contexts. Patient and Doctor profiles are the two types of user profiles that are used. Patients may utilise their patient profile to schedule appointments, make payments, read reports, and examine their medical and financial history. Employees can access the patient profile, operation planning, and patient tracking systems using the doctor module's User Interface (UI). There is also an Admin user profile, which is responsible for adding people to the database and granting access based on their classification. Users with Doctor access can read his patients' information, write prescriptions, and access the patient's electronic medical records. There is also another feature that can be accessed by all the users collectively including the Doctor and the Patients called the disease prediction system. The inclusion of techniques such as data mining, data analysis, data science, DL, and ML has been proven to be quite useful in fields such as bio-sciences and healthcare.

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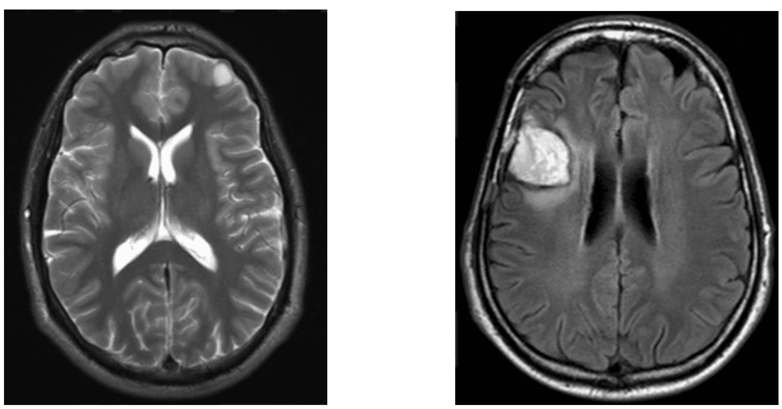
B. Disease Detection Models

Medical image analysis plays a crucial role in the clinical diagnosis of a variety of illnesses, including brain tumour, skin cancer, breast cancer, liver tumour, pancreatic tumour and recently covid-19. The need for a user friendly and multi disease prediction model is something to look forward to where a person can find all the disease prediction models in one place. Such multi disease prediction models can be developed with the help of proposed models and methodology that have been developed by studying various effective algorithms that can provide us with a prediction of a disease with high accuracy. The input layer, feature map layer, hidden layer, and output layer make up the DNN. These disease detection models have been developed individually and then merged with a single server using a flask web framework. The disease detection models that have been developed are going to detect three diseases that are brain tumour, pancreatic tumour, and coronavirus.

1) *Brain Tumour Detection:* Early location of Brain tumours is exceptionally needed to give treatment to patients. The patient's life chances are improved by its early identification. The way toward diagnosing the mind tumours by the doctors is regularly done utilizing a manual method of division. It is tedious and a troublesome one. To tackle these issues, masked Region-based CNN (RCNN) is utilized in the development of the brain tumour detection model. The essential point is to introduce streamlining based MRI scan's picture division. Little parts permit the plan in a profound design. It has a positive result regarding over-fitting gave the lesser loads are relegated to the organization. Skull stripping and picture improvement calculations are utilized for pre-handling. The trial result shows the better exhibition while contrasting and the current techniques. The looked at boundaries are exactness, review and precision. In future, diverse choosing plans can be embraced to improve the precision [22].

a) *Dataset:* To train an accurate and optimized model there are a set of steps that need to be followed which have been discussed above in section four. The dataset further needs to be divided into training, testing and validation data. The dataset needs to be divided into the right ratio to ensure a better and accurate model. For the brain tumour detection model, we have made use of the BraTS 2020 dataset and divided into the three types. We divided our dataset into three parts: 70 percent training, 20 percent validation, and 10 percent testing.



(a) (b)

Fig. 2: (a) MRI scan with a Normal Brain [23] (b) MRI scan with a Brain Tumour [23]

b) *Mask RCNN for Brain Tumour Detection:* The recommended approach is resilient against variations in size, shape, and over-lapping tumour borders with general brain tissues even when there are MRI abnormalities such as noisy, bias field effect, and various acquisition angles. We offer an automated approach for increasing the resilience of brain tumour recognition and segmentation in this work, which makes use of the Mask RCNN [24]. Mask RCNN is a technique for image segmentation that reliably recognize items in an image and creates an increased segmentation mask to every occurrence. Instance segmentation and semantic segmentation are two types of segmentation available in Mask RCNN. Mask RCNN was used in the proposed Model for instance segmentation since it aids in feature extraction and segmentation of each image instance. Mask RCNN is indeed a Faster RCNN modification that works by combining an existent branch for bounding box detection with a branch for estimating an object mask (Region of Interest). Mask RCNN beats all existing single model entries on every test and has considerably fewer over-fit scenarios than Faster RCNN [25]. Skull removal to avoid detecting bones and background removal by discovering extreme points in shapes has been done as data pre-processing steps for this model.

c) *Feature Extraction:* Feature extraction is a research methodology in which a large volume of raw data is reduced to a smaller number of well-managed classes for processing. The backbone network was used to extract useful details from the input of MRI scans. A branch of the Mask RCNN is dedicated to classification and boundary-based regression. Because ResNet 101 can generate a convolution neural network with 101 deep layers, it is used to extract information from a picture. When we apply ResNet 101 instead of the standard CNN model, we gain a 26% relative improvement. When a CNN model was used on larger and deeper datasets, it highlighted a concern about deterioration, as the accuracy became saturated as the depth is increased. The region of interest is created utilizing the proposed network for the region proposed network (RPN). The area recommended network suggested network does have advantage of being able to identify objects on any dataset, which makes it useful for model end-to-end training. A 3 by 3 convolution operation scans the picture pixel by pixel to give relevant inputs that represent the bounding box with varying widths and are spread throughout the image. There are around 20 thousand anchors with various scales and sizes that relate to one another to cover the image. To identify if an anchor includes the object or perhaps the background, binary segmentation is employed. The BBR produces bounding boxes based on the value of the Intersection-over-Union (IoU). Positive anchors (FG class) have an IoU larger than 0.7 with a ground-truth (GT) box, while negative anchors have an IoU less than 0.7 [26].

d) *Bounding Box Regression and Classification of Region of Interest (RoI):* The input to the network that has been developed is given as feature mapped image of dataset and proposed RoI which was generated from previous section. The two classes that the specific input image will be classified into will be tumour and no tumour, this network increases the bounding box's area even further. The bounding box helps in locating and measures the size of the tumour, with the help of the bounding box regression we can further refine our results which further assists in encapsulating the tumour region. We'll get a feature map out of this, which will be downward sampled k times from the original picture size using convolution. This is done to avoid the incident of coincidence of RoI granularity with the feature map. The RoI align layer normalizes feature maps by getting the fixed size of key point vectors for arbitrarily defined potential areas and conducting bi-linear interpolation to address misalignment issues that arise when the RoI pooling layer uses the quantization operation. To acquire the final recognition results, these feature points are categorized and regressed in layers of regression and classification.

e) *Segmentation Mask Acquisition:* From here, we'll develop the model's classification and regression branches before moving on to the mask branch. The RoI classifier's outputs are used as input in this segmentation network, and the result is a segmentation mask with a precise resolution of 28 × 28 pixels. This mask of 28 × 28 pixels contain more information over binary masks due to the presence of floating numbers. During the training stage, the ground truth the masks have been reduced in size to 28 × 28 pixels to calculate the loss using the expected mask. During inference, the predicted mask is resized to fit the bounding box of the RoI, resulting in the final output mask. The objective of segmentation is to find and segment the brain tumour in a complicated backdrop without requiring operator intervention. Using the Mask RCNN, we hope to predict whether MRI scans contain tumour or non-tumour regions. Below are three examples from the training set of segmented images of the tumour that is lying underneath. The red portion signifies the tumour region of the MRI scan.

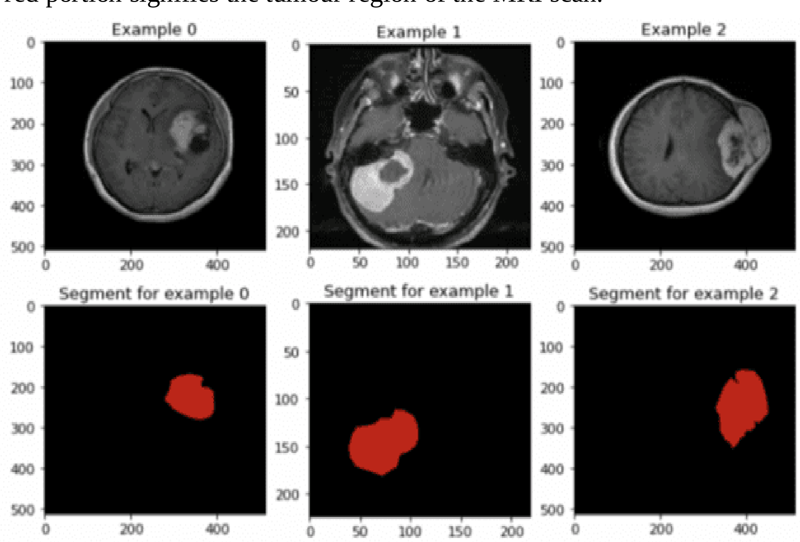
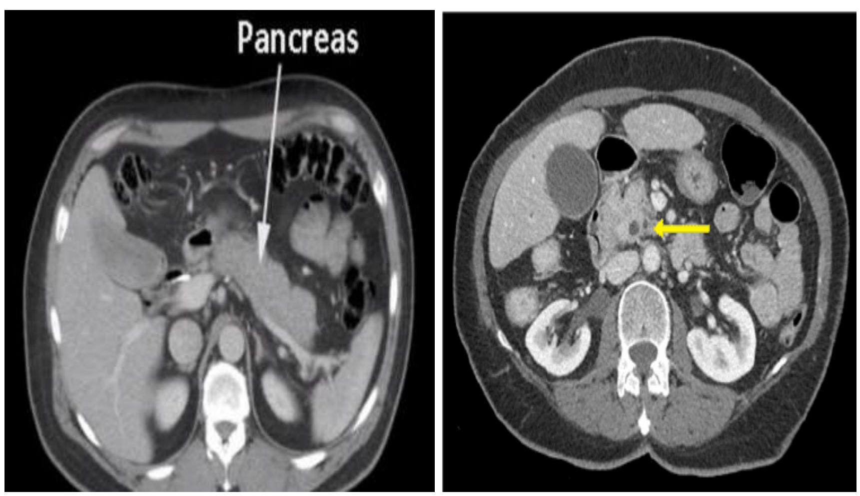


Fig. 3: Examples of the training set and Brain tumour region

2) *Pancreatic Tumour:* Pancreatic Tumour is considered one of the major causes of death in the globe. In the United States, 61,450 people are anticipated to be diagnosed with pancreatic cancer (32,960 men and 28,490 women). This type of cancer accounts for around 3.01% of all cancers. This cancer is the eighth most frequent cancer among women and the tenth most common cancer among males. CT scans is widely utilized in the investigation and detection of pancreatic cancers. The detriment of X-ray is long tedious in the manual decision by a radiologist. Robotized classifiers can refresh the analysis action, as far as both precision and time need [27]. This model that has been developed utilizes machine learning algorithms called minimum distance classifier and CNN. Tumours of the pancreas are particularly difficult to detect since they are placed deep in the abdomen and hidden behind a number of organs. Pancreatic cancer has the lowest 5-year survival rate, which is about 9%. As a result, it is critical to discover cancer tumours at an early stage so that the patient can receive correct diagnosis and treatment, and humanity can prevail over this devastating and fatal disease. A few symptomatic methods, like as imaging studies and blood tests, may be used to identify whether there is a tumour in the pancreas. Understanding the tumour's stage (severity) is crucial to selecting the optimal treatment. A CT scan can help you decide whether surgery is the best option for you. When the pancreas is covered by a smaller portion of the abdomen, early detection becomes difficult, and using a detection and segmentation model becomes problematic [28]. Using a convolution neural network model, we provide a unique technique for training and identifying tumours from pictures in this study.

a) *Dataset:* The dataset is made up of 1500 CT scans that were gathered from the website medical decathlon and pre-processed utilizing image processing techniques like denoising and augmentation. The dataset is made up of CT scan images of tumours and non-tumour scans that are fed into the algorithm as input. These photographs were originally in 3-D format (.nii file extension), but we converted them to 2-D format (.jpg file extension). Image pre-processing is done to improve the quality of the dataset such as removing the mean RGB value and data augmentation, which is very useful in medical picture analysis, such as collecting random patches from the original image and horizontally flipping them in the image. The training and testing sets were separated from the rest of the dataset. The training set included 70 percent of total of the pictures, which totalled 1000, while the testing set included 30 percent of the images, which totalled 500.



(a) (b)

Fig. 4: (a) CT scan with a Normal Pancreas[29] (b) CT scan with a Pancreatic tumour [29]

b) *Feature Extraction:* The truth is that CNNs offer automated feature extraction, which is their main benefit. During the training stage, the CNN method comprises extraction of features and weight computation. A number of parameters must be changed during back propagation, which reduces the number of connections inside the neural network architecture. The CNN feature extractor is made up of several types of neural networks that determine the weights throughout the training phase. An epoch is a machine learning phrase that refers to how many passes the machine learning algorithm has made across the whole training dataset. Batches are commonly used to organise huge data collections [30]. The number of epoch we have trained during the algorithm development were 15 and the training and testing of a deep learning network's process takes longer in general. During the training stage, this instructs the system to learn based on the classes defined in the image. Once the system has learned how to categorize data based on the attributes provided, it may assign the test data to one of the classes. Because CNNs can automatically create characteristics from dataset and frequencies represent images, they are most often used in healthcare systems. Following that, these features are put into a classifier network, which performs classification and regression. In the employed CNN model, we trained a CNN to discriminate pancreatic cancer from healthy pancreases using contrast enhanced-CT images of patients. Neural networks use a hierarchy of neurons with activation functions and variables to extract and synthesize information from images and construct a model that represents the intricate relationship between visuals and diagnosis. CNN offers the potential to develop machine detection and diagnostic procedures for pancreatic cancer to help radiologist interpretation. In a convolutional neural network, the first layer is the convolution layer, which applies filters to the top image or new feature regions. The bulk of such user-specified characteristics are situated here in the network. The most important qualities are the quantity of kernels and the size of the kernels. Pooling layers, which are similar to convolutional layers but have a particular purpose, like max pooling, that gets the greatest value in a filter area, or average pooling, which takes the average value in a filter area, are the second type of layer in a deep CNN. These are commonly used to reduce the complexity of a network. The fully connected layers, the third type of layer in a deep CNN, can be employed to smooth the findings before classification and are placed just before CNN's implementation. So, the first convolution layer in a CNN learns fundamental characteristics like detection filters like edges, corners, and so on. The pooling layers learn the filters that identify distinct sections of the objects, in our instance kidney, abdomen, liver, and so on. After that, the fully linked layer provides better representations of object recognition from within the picture [31].

c) *CNN for Pancreatic Tumour Detection:* In medical image analysis, image classification has emerged as a major approach for early detection and prediction. We have attempted to devise a novel way to building a tumour detection model combining image pre-processing techniques and CNN model architecture in this proposed model. The CNN model architecture is used to train and test the data in order to distinguish between tumour and non-tumour regions. The dataset is made up of CT scan images of tumours and non-tumour scans that are fed into the algorithm as input. This was done for the system's picture enhancement and pre-processing procedures. Because of its versatility and precision, CNN has proved to be highly beneficial in the field of medical image classification. The convolution neural network consists of the pooling layers, neural layers and a soft-max layer. Another important area to explore while creating a deep learning CNN model is the activation function. The activation function is a non-linear change that we apply to the input before passing it to the next layer of neurons or converting it to output. In this model, we have used the ReLU activation function. ReLU stands for rectified linear activation function, which has become a linear activation function mostly employed in CNN’s for giving the output of the input directly, otherwise the output will become zero. Models created with the ReLU activation function are easy to train and often achieves better accuracy and confusion matrix.

d) *CNN Model Result:* Detecting pancreatic tumours using the abdominal CT scans becomes harder as pancreas are a smaller part of the body. The CNN model was built on python 3.8 and the libraries used for this model training and testing was tensor-flow version 2.7 and keras version 2.4. As the optimization algorithm, Adam optimizer is used to train the neural network. A neural network that is created and trained to learn as per the classes defined with in picture may be used for classification. The two main classes named in this system of dataset are tumour and no tumour. Once the system learns the classification done based on the features given to it, it can then classify the test data into one of those classes. For classification of the tumour region, the various organs will need to be identified. A certain abdominal CT scan consists of the following parts such as: pancreas, liver, kidney, vertebra, stomach, spleen, fats, liquid and the lining. With the model being trained with the mean value of all these areas are calculated. The classifier is given these numbers as thresholds for classifying distinct organs. Because it takes less time to train and has higher accuracy, the sequential CNN model of neural network is adopted. The number of trainable components in your network, or neurons that are affected by backpropagation, is referred to as trainable parameters. An epoch is a period of measurement used only to train the neural network for a single cycle utilising all of the training data. We use all of the data exactly once in each period. A forward and backward pass make up one pass: An epoch is made up of one or more batches, each of which trains the neural network on a subset of the dataset. The total number of trainable parameters are 8,485,218, the number of epochs was 20 and the batch size of each was 35. The extracted features map seems to have a different dimension of 224 × 224, and it is sent to a max-pooling layer. The training accuracy of the model to detect the tumour is 92%. Some of the outputs of the model is shown below in Fig. 5.

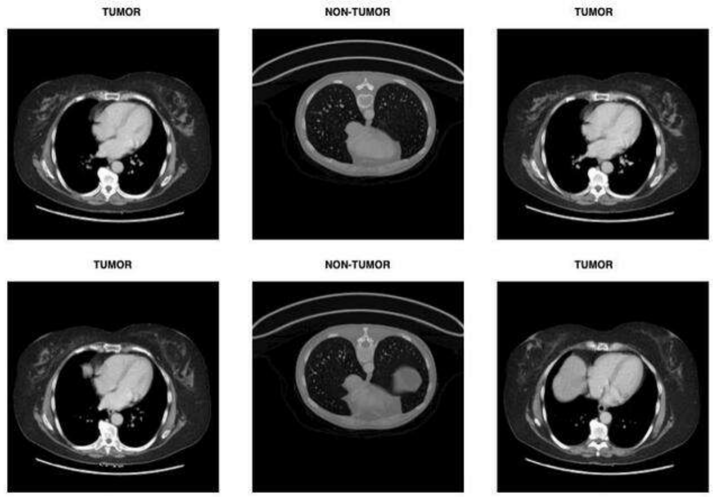
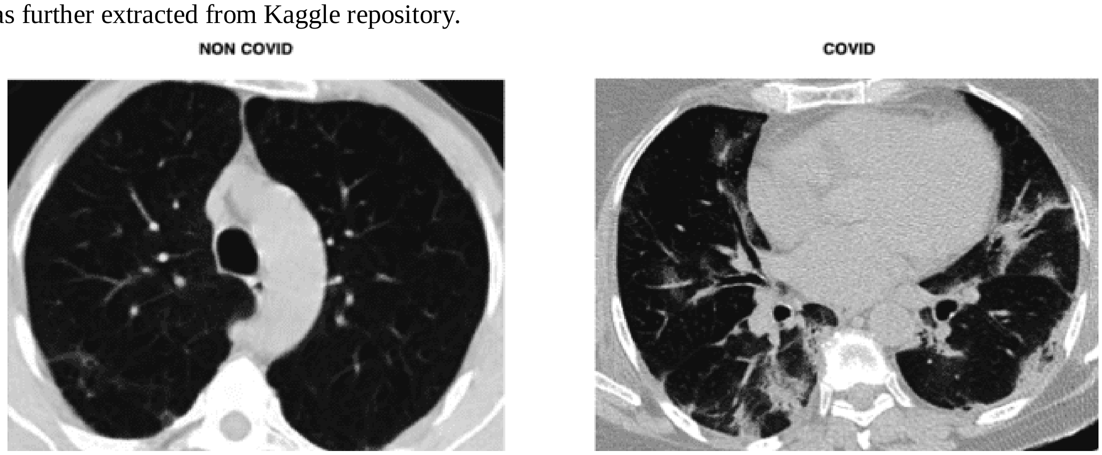


Fig. 5: Detection of pancreatic tumour using CT scans

3) *Covid-19 Detection:* SARS-Covid, also known as Covid-19 started in Hubei, China, and soon spread throughout the world, causing a worldwide epidemic. The reaction has been a confused mix of primarily turmoil with a little good faith thrown in for good measure. Individuals all across the world secluded together to limit the spread of the sickness, with researchers hastily sharing the pathogen's whole DNA. The obstacles to collaboration have been decreased by researchers. Despite this, the epidemic has had several detrimental repercussions. Emergency departments have been overwhelmed as a result of the fast contamination and lack of assets, which has caused significant worry among medical personnel. The overall number of reported instances of the illness had surpassed 39,500,000 in over 180 nations as of November 2020, although the number of individuals affected is most likely far higher. Covid-19 has claimed the lives of almost 1,110,000 people. This epidemic continues to put clinical frameworks around the world to the test in a variety of ways, including rapid increases in requests for medical clinic beds and basic shortages in clinical equipment, as well as the contamination of many medical care workers. As a result, the limit in terms of rapid clinical decisions and persuasive utilization of medical services assets is crucial which is the reason why a disease prediction model has been developed on this disease [32].

a) *Dataset:* We will employ the CT scans to create a covid-19 disease predictor model in the covid-19 detection model. Normal and covid-19 positive CT scans are among the two types of Image Dataset Folders that are available in the A total of 2475 CT scans were included in the SARS-covid CT scan dataset, including 1250 CT scans positive for covid-19 and 1225 CT scans for individuals who were not diagnosed with covid-19. The dataset was initially meant to promote R&D in the field of artificial intelligence systems that can determine whether a person is infected with covid-19 by analysing his or her CT scans. The dataset was further extracted from Kaggle repository.



(a) (b)

Fig. 6: (a) CT scan with a Normal Diagnosis[33] (b) CT scan with a Covid-19 [33]

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b) *ResNet-50 for Covid-19 Detection:* In this disease detection model, the illness Covid-19 is detected utilising a 50 layers deep convolutional neural network ResNet-50. ResNet is regarded as a superior deep learning architecture since it is relatively simple to optimise and achieves higher accuracy. Furthermore, there is always the issue of diminishing gradient, which is overcome by employing the network's skip connections. The temporal complexity of the network grows as the number of layers in the deep network architecture grows. The use of a bottleneck design can help to reduce this complexity [34]. As a result, we chose the ResNet-50 pretrained model to construct our framework and excluded alternative pretrained networks with more layers. Resnet-50 captures the most important aspects of an image and can be applied to similar and smaller datasets. This reusability feature of a pre-trained model not only saves time, but it also saves money when the training dataset is limited. All photos in the collection have been rescaled to 224 × 224 × 3 pixels. The goal of rescaling the image is to employ iteratively in the ResNet-50 model's numerous phases. Mean and standard deviation approaches are used to standardise the images in the ImageNet collection.

c) *Feature Extraction and Model Result:* The network is initially fine-tuned by resizing the images. In addition, the ImageNet dataset is always growing, resulting in a larger training set. Instead of manually separating image learning rates, the Cyclical Learning Rate approach is used. This strategy is used to maximize learning rate optimization. Images from the input dataset are scaled to 224 × 224 × 3 pixels. Using a discriminative learning rate for 50 epochs, the entire network is fine-tuned. It is usually useful to train the model iteratively using the progressive resizing technique. With a total sample size of 32, the Adam optimizer is utilized during training. The FastAI framework is important for data pre-processing, data augmentation, and, most crucially, training [35]. The final accuracy achieved using this method was 88%.

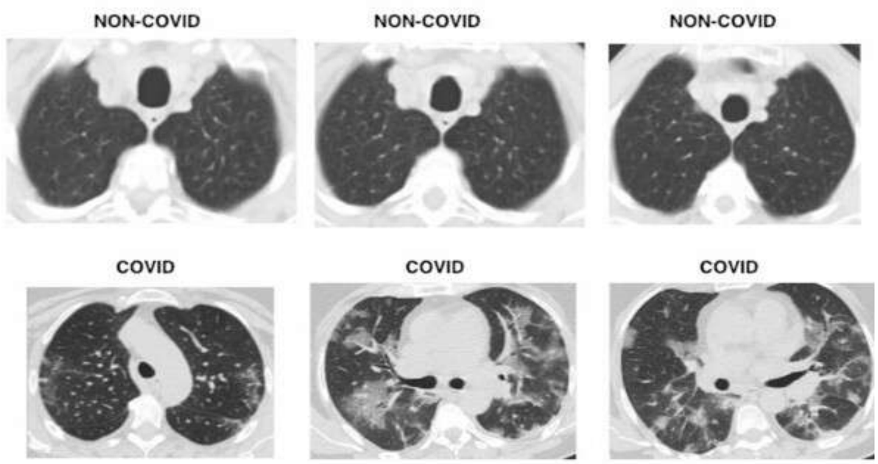

Fig. 7: Detection of Covid - 19 using Chest X-Rays scans

V. RESULTS AND DISCUSSION

The proposed Healthcare Management System acts as digital platform which is aimed to be is user friendly, adaptable and affordable. This system addresses real-world problems faced by various individuals in the healthcare industry today. To support the idea of integrating all the three different disease detection models on a single server, we firstly stressed on some of the additional features on the server as the basic approach, the idea was to create a Web Responsive application where there is a wide range of features made available revolving around AI and Deep Learning so that the user can automate easy to do tasks, these solutions will help surgeons, patients and care teams throughout the patient journey by automating some of the crucial tasks done manually such as decision making, post-surgery planning, tracking and estimating recovery-time, and takes patients' feedback. Collectively which would be a go-to platform for users of wide range in terms of Age, Profession, Gender etc. The proposed healthcare management system aims to create a digital platform that can aid in accelerating the process of medical treatments, and bridge the gap between a patient and a doctor throughout the process. Digital health offers the ability to help individuals monitor and manage chronic illnesses while also preventing disease and lowering healthcare expenses. It may also personalize medication for each patient.
Advances in digital health can also help healthcare professionals to reach a more conclusive decision and provide with the right medical opinion to their patients. The proposed system has been designed using Artificial Intelligence and Cloud Computing tools so that the patient alone can also utilize this platform and cater to his/her needs. Further in this section, we have attached the Screen-shots to show the entire working of the Smart Healthcare Management System.

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We will see the homepage, the login page and a brief walk through of the different disease prediction models. The major reason we have performed our work surrounding these three diseases is their survival rates which are known to be very low and such work can really make an impact in the society by saving lives. Early detection of these three diseases alone can save close to 600,000 lives every year.

The proposed system is described as follows [36].

1) Homepage for the Smart Healthcare Management System which has been designed specifically using the flowchart figure. All the features are available over here such as Doctors Portal, Patient Portal, User Feedback, Emergency Surgery on Site (SoS) and Disease Detection Models.

Fig. 8: Screen-shot of the Homepage of Healthcare Management System

2) Fig. 9 shows the Screen-shot of the drop down menu for the Doctor portal and the working of the AI-powered chatbot that has been deployed on the Web Application for the proposed healthcare management system as discussed in Fig. 1. This AI-powered chatbot act like a digital assistant for the users. This chatbot is created in such a way that it can help the user navigate around the website, it can turn out to be extremely useful for a first-time user. This portal will be used by registered doctors to save their documents, keep track of their patients' progress, and so on. The user will have access to conventional measures such as changing passwords and using two-factor authentication to ensure the security of their account. The doctor portal features a function that allows the doctor to send tailored messages to the patient, checking on his recuperation and receiving timely information, with the goal of bringing the patient and doctor together on a single platform. This will allow the Doctor and the Patient to communicate more effectively and understand each other. Surgery planning is another important aspect of this undertaking. The doctor can reserve an Operating Theatre or a Surgery Room using the Doctor Portal for a specific time period and dates. In addition, the Doctor can also beforehand request for a support team for the surgery. This support team will consist of a surgeon's assistant, an anaesthetist, a circulating nurse and a surgical technologist.

Fig. 9: Screen-shot of the drop down menu for the Doctor Portal

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3) Fig. 10 shows the Screen-shot of the drop down menu for the Emergency SOS services as discussed in Fig. 1. This emergency SOS services provides features such as an emergency appointment, and emergency doctor. An emergency doctor is available 24 hours a day, seven days a week on a zoom call to assist the patient in emergency situations. Another aspect of the Emergency SOS is that the user can skip lines and manual form filling by going, they can simply go to the website and check the status of the availability of room, such as ICU or emergency room beds well in advance, as well as choosing a particular desired doctor to consult. Besides the Emergency SOS, there is also menu for the feedback feature which has been made available on the smart healthcare management system as discussed in Figure 1. Here the user, simply by filling a short survey can drop feedback's of the website including User Experience and User Interface. It would help entail their level of contentment with the product, and can be proved useful for improvising the product.

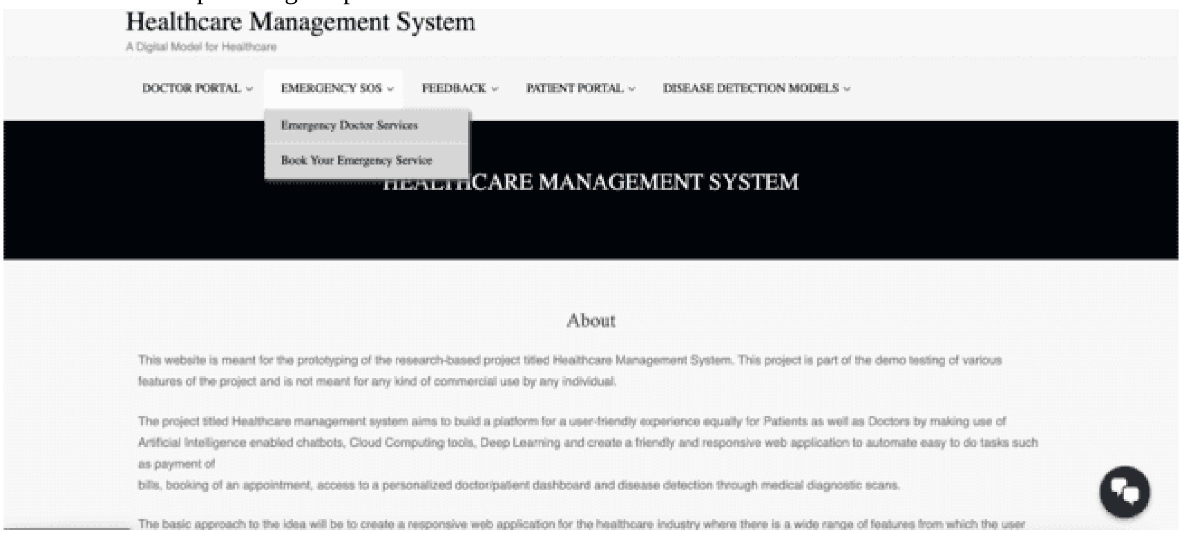

Fig. 10: Screen-shot of the drop down menu for the Emergency SOS services

4) Fig. 11 shows the Screen-shot of the drop down menu for the Patient portal as discussed in Fig. 1. The patient portal is designed so as to let the patient make complete use of the features provided on the platform such as booking an appointment, emergency SOS services and also access to health record or reports. Every patient will be given a personalised dashboard where they will be able to access all of their personal health specific information's. Personal information, concerned Doctor details, medical test reports, X-rays, MRI scans, Illness description, thorough diagnosis of the patient, precautions, updated prescriptions, road to recovery, and other directions given by the Doctor that the patient must follow will all be available on the patient's dashboard.

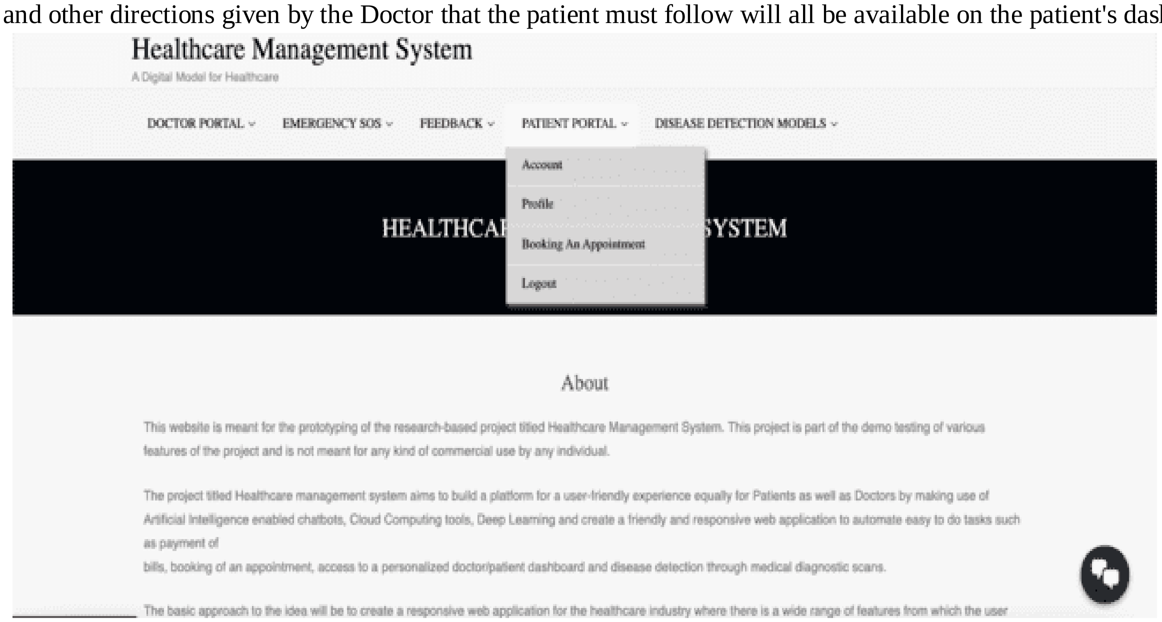

Fig. 11: Screen-shot of the drop down menu for the Patient Portal

5) Fig. 12 shows the Screen-shot of the Homepage for the proposed Smart Healthcare Management System along with the drop down menu for the Disease Detection Models. The disease detection models have been built based on three diseases which are namely, Brain Tumour, Pancreatic Tumour and Covid-19. Once the user clicks on the choice of disease detection model he/she wants to use they will be taken to the next page where the chosen disease prediction model has been deployed.

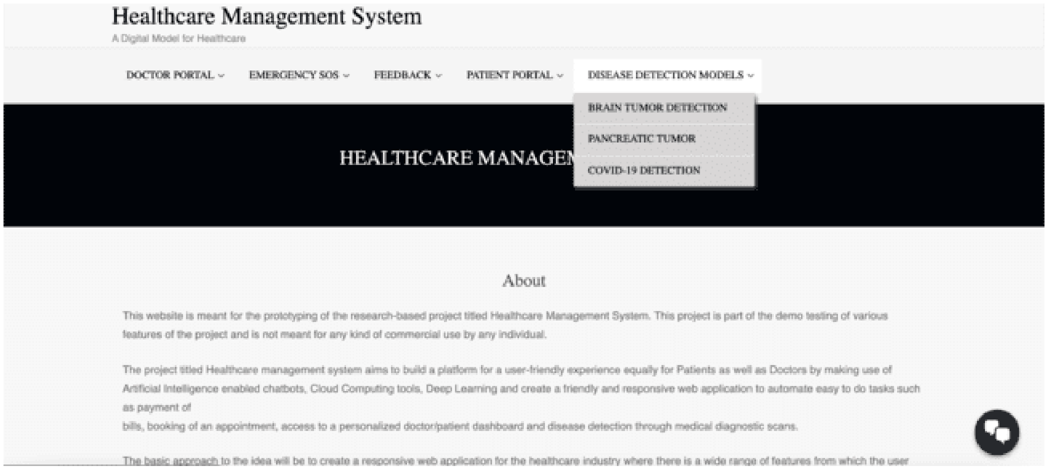

Fig. 12: Screen-shot of the Disease Detection Model Dropdown menu

6) Fig. 13 shows the header page for Brain Tumour Disease Detection. Once the user has logged in, on the right hand top of the menu the user can navigate to the disease detection model of his/her choice from the three.

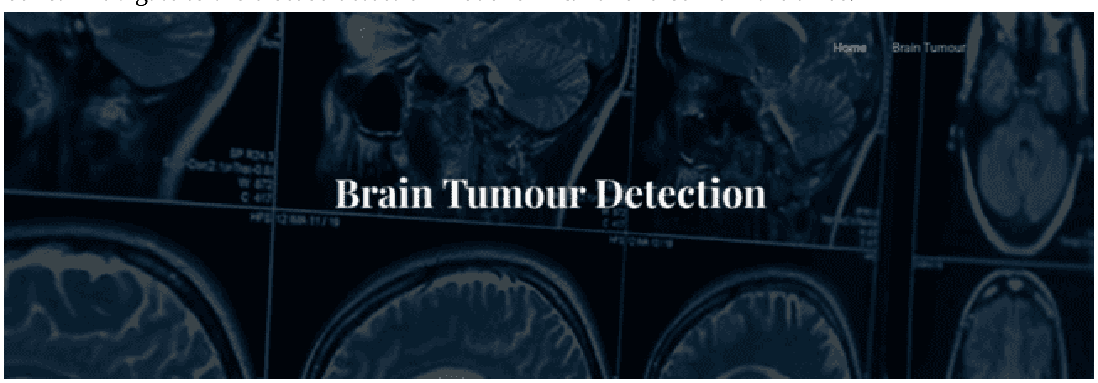

Fig. 13: Screen-shot of the Brain Tumour Disease Detection Header Page

7) Fig. 14 shows the page for Brain Tumour Detection, the user needs to scroll down to the Screen-shot shown below. Over here there is a brief description about Brain Tumour and the user can use the "choose file" button to navigate to the image in their local machine and can select the scanned image in "JPG" or "PNG" format. Once the file has been selected from the local machine and now the user will need to press the submit button, which would trigger the trained model and then with high accuracy display the results on the next page automatically.

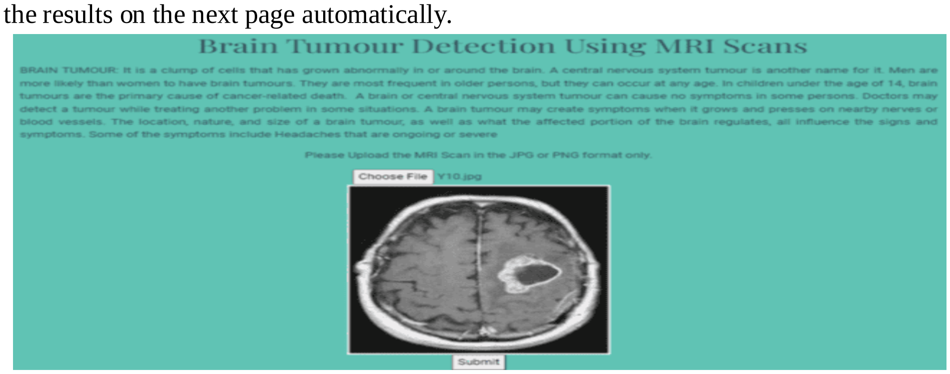

Fig. 14: Screen-shot of Selecting the File page for or Brain Tumour Disease Detection

8) Fig. 15 shows the result page for Brain Tumour Disease Prediction. This page will display the result that has been predicted in this case weather the uploaded scan has been diagnosed with a Brain tumour or not. The model that has been deployed on the server for Brain Tumour Detection has been developed using the Mask RCNN methodology and has an accuracy of 91% as discussed in section 4.2. Also, in cases when the report is Positive, there would also be a list of doctors which the user can consult immediately for specialist opinions, for the sake of prototype a random list from our self-assembled database has been displayed.

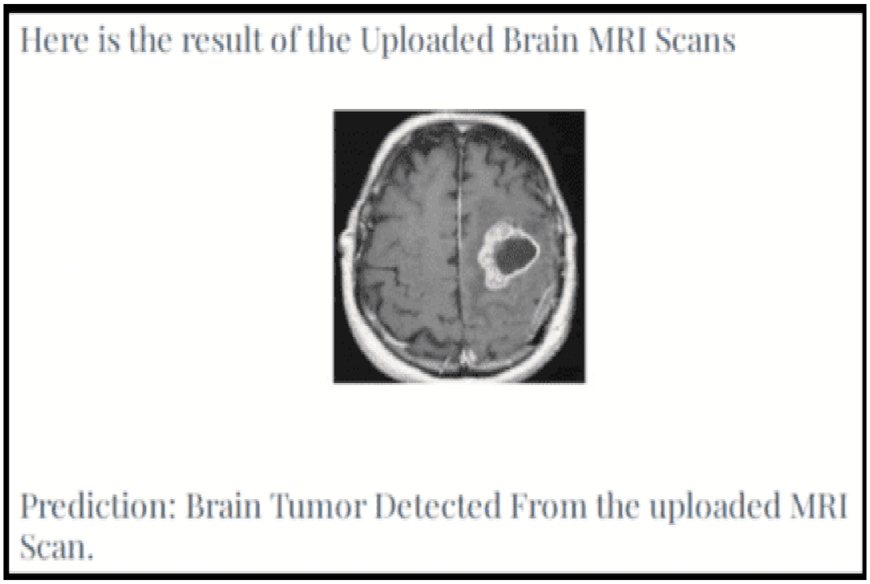

Fig. 15: Screen-shot of the Predicted Output for Brain Tumour Disease Detection

9) Fig. 16 shows the header page for Pancreatic Tumour Disease Detection. Once the user has logged in, on the right-hand top of the menu the user can navigate to the disease detection model of his/her choice from the three. In the next few Screen-shots, we will see the working of the Pancreatic Tumour Disease Detection using Deep Learning. It follows similar steps as to Brain Tumour.

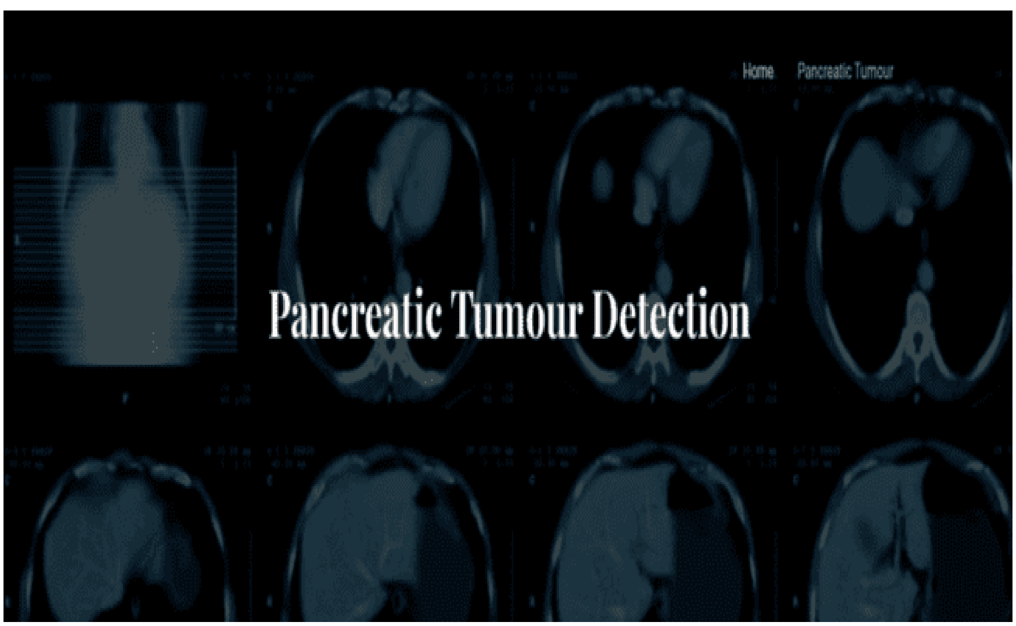

Fig. 16: Screen-shot of the Pancreatic Tumour Disease Detection Header Page

10) Fig. 17 the body of the page for Pancreatic Tumour Disease Detection. From the above Fig. 16 the user needs to scroll down to the Screen-shot shown below. Over here there is a brief description about Pancreatic Tumour and the user can use the "choose file" button to navigate the image in their local machine and can select the scan image of that particular disease in "JPG" or "PNG" format. Once the file has been selected from the local machine and now the user will need to press the submit button, which would trigger the trained model and then with high accuracy display the results on the next page automatically.

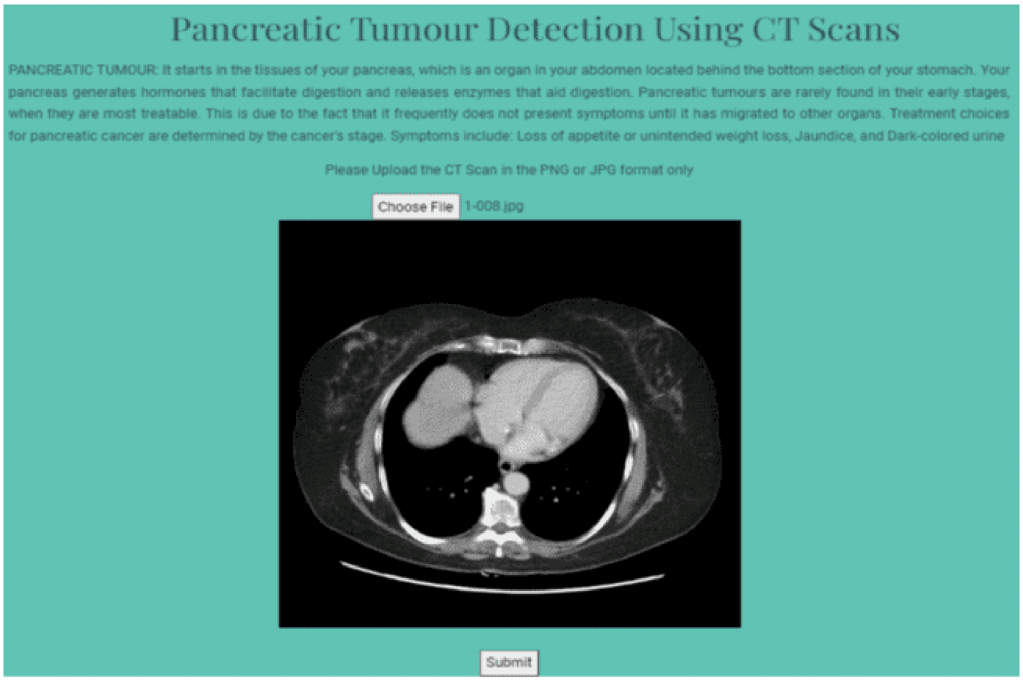

Fig. 17: Screen-shot of Selected File for Prediction in Pancreatic Tumour Detection

11) Fig. 18 shows the result page for Pancreatic Tumour Disease Detection. This page will display the result that has been predicted in this case weather the uploaded scan has been diagnosed with a Pancreatic Tumour or not. The model that has been deployed on the server for Brain Pancreatic Tumour Detection has been developed using the CNN methodology and has an accuracy of 92% as discussed in section 4.2. Also, in cases when the report is Positive, there would also be a list of doctors which the user can consult immediately for specialist opinions, for the sake of prototype a random list from our self-assembled database has been displayed.

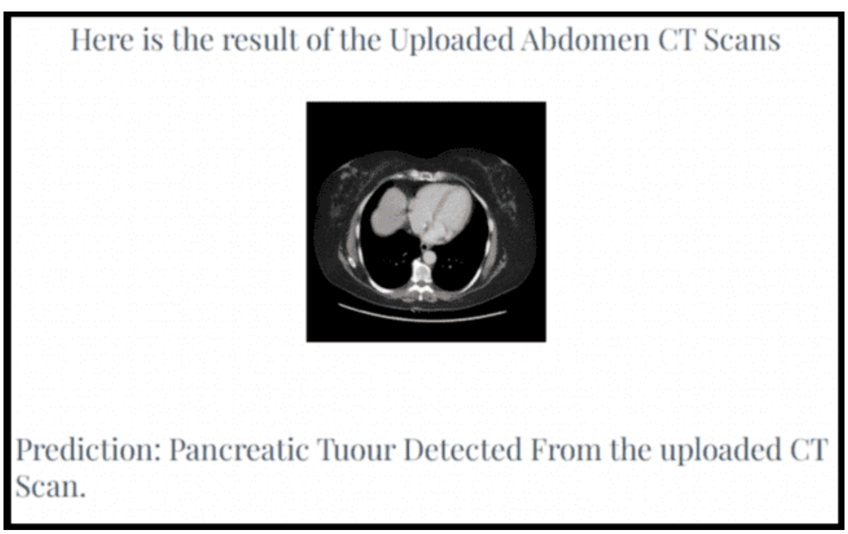

Fig. 18: Screen-shot of Selected File for Prediction in Pancreatic Tumour Detection

12) Fig. 19 shows the header page for Covid-19 Disease Detection. Once the user has logged in, on the right hand top of the menu the user can navigate to the disease detection model of his/her choice from the three. In the next few Screen-shots we will see the working of the Covid-19 Disease Detection using Deep Learning. It follows similar steps as to Brain Tumour.

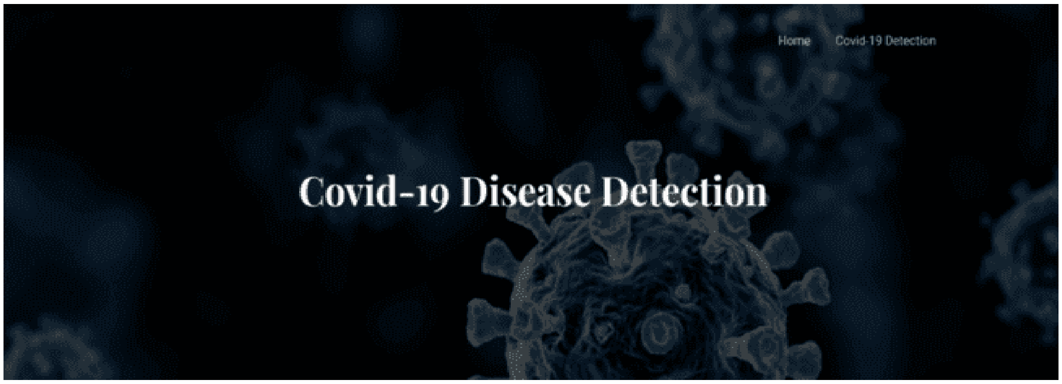

Fig. 19: Screen-shot of Covid - 19 Disease Detection Header Page

13) Fig. 20 shows the body of the page for Pancreatic Tumour Disease Detection. From the above Fig. 19, the user needs to scroll down to the Screen-shot shown below. Over here there is a brief description about Pancreatic Tumour and the user can use the "choose file" button to navigate the image in their local machine and can select the scan image of that particular disease in "JPG" or "PNG" format.

Fig. 20: Screen-shot of Upload the Scan Page for Covid-19 Disease Detection

14) Fig. 21 shows the page for Covid-19 Disease Detection, once the file has been selected from the local machine and now the user will need to press the submit button, which would trigger the trained model and then the results would be displayed with high accuracy on the next page.

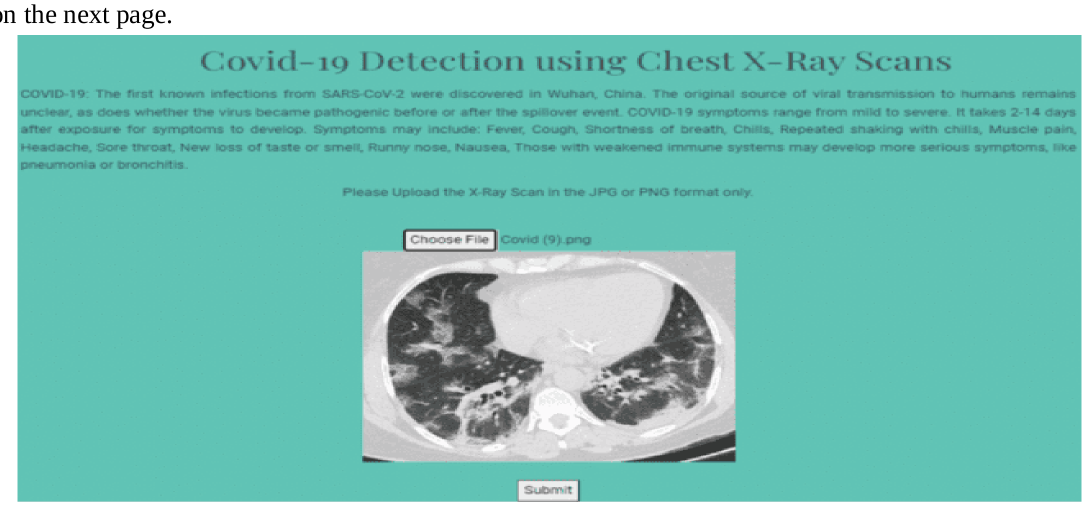

Fig. 21: Screen-shot of the Selected File for Prediction in Covid-19 Disease Detection

15) Fig. 22 shows the result page for Covid-19 Disease Detection. This page will display the result that has been predicted in this case weather the uploaded scan has been diagnosed with a Covid-19 or not. The model that has been deployed on the server for Covid-19 Disease Detection has been developed using the ResNet methodology and has an accuracy of 88% as discussed in section 4.2. Also in cases when the report is Positive, there would also be a list of Doctors which the user can consult immediately for specialist opinions, for the sake of prototype a random list from our self-assembled database has been displayed.

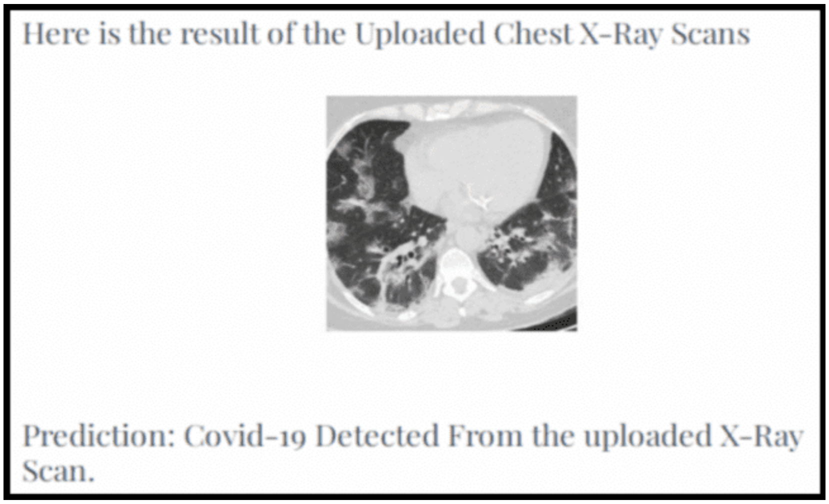

Fig. 22: Screen-shot of Predicted Output for Covid-19 Disease Detection

16) *Parameters for performance evaluation:* We have used parameters that are widely employed in the field of ML (Machine Learning) and medical image processing. For classification, we employed three distinct machine learning methodologies: Mask RCNN, CNN, and ResNet-50, and compared the results for each classifier. We employed Accuracy, F1 Score, and Precision to assess the performance of disease detection models.

Table 1: Performance evaluation of the developed disease detection models

Disease Prediction Models	Accuracy Proposed by Author	Experimental Accuracy	Precision Proposed by Author	Experimental Precision	F1 score proposed by Author	Experimental F1 Score
Brain Tumour Detection using Mask RCNN [37] (BRATS 2020 Dataset)	0.95	0.91	0.95	0.91	0.92	0.90
Pancreatic Tumour Detection using CNN [38] (PLCO Pancreas Dataset from NIH)	0.97	0.92	0.95	0.93	0.96	0.94
Covid-19 Detection using ResNet-50 [39] (UTKML 2021 Kaggle Dataset)	0.94	0.88	0.90	0.89	0.93	0.92

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17) Confusion Matrix of the Disease Detection Models: The confusion matrix of Brain Tumour has further been used for evaluating the performance of the model. An $N \times N$ matrix is used to evaluate the performance of a classification model, where N is the number of target classes which in our case are 2. The matrix compares the actual goal values to the machine learning model's predictions.

a) Fig. 23 shows the confusion matrix of the Brain Tumour Detection Model. The confusion matrix of Brain Tumour has further been used for evaluating the performance of the model.

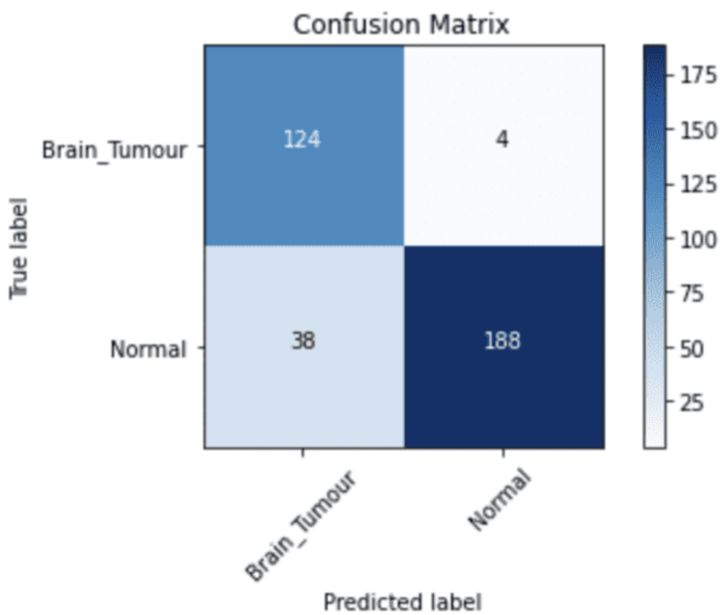

Fig. 23: Confusion matrix of the Brain Tumour Detection Model

b) Fig. 24 shows the confusion matrix of the Pancreatic Tumour Detection Model.

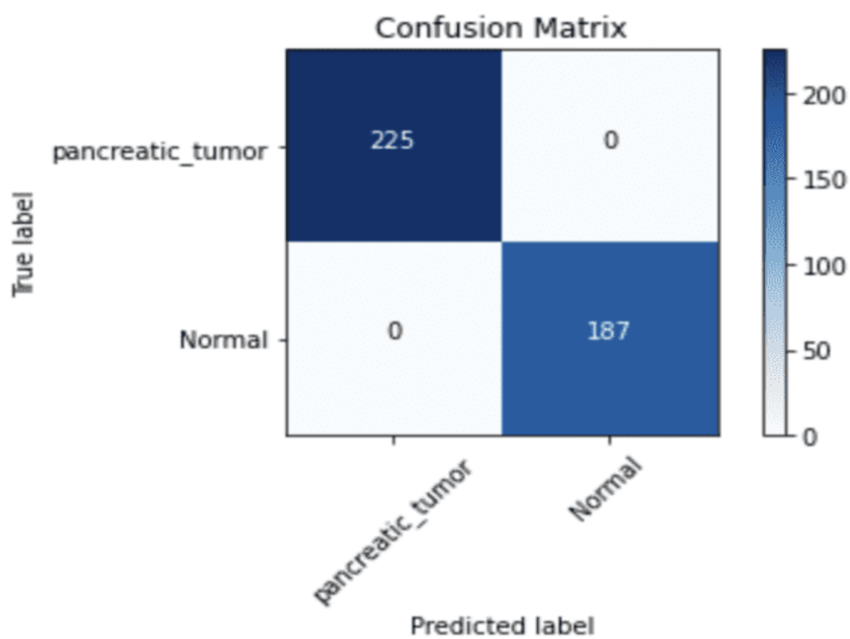

Fig 24: Confusion Matrix for the Pancreatic Tumour Detection Model

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c) Fig. 25 shows the confusion matrix of the Covid-19 Disease Detection Model.

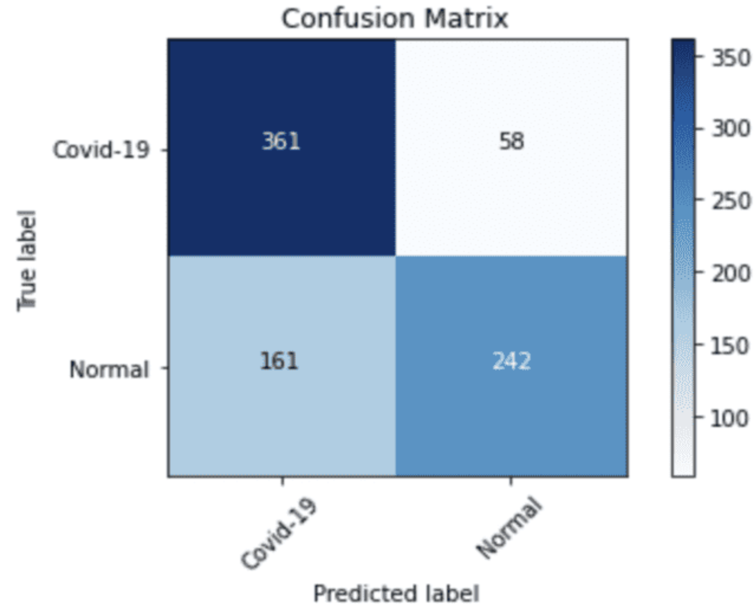

Fig. 25: Confusion Matrix for Covid-19 Disease Detection Model

VI. CONCLUSION

By providing a comprehensive and customised approach to delivering treatment, regardless of location, digital health can revolutionise the patient experience and address access barriers. The foundation of this goal is the creation of a unified, data-driven, pan-India health system. In this paper, we propose a way for digitalizing healthcare by unifying the healthcare industry and bringing it on a single platform. Unifying the healthcare industry means bringing the clinics, hospitals, diagnostic services, pharmacy services, and hospital admission services on one single platform. The features that have been developed on our platform such as support in automating some of the critical processes that are now done manually, including decision-making, post-surgery planning, tracking, estimating recovery time, and smart disease detection using deep learning. We employed a Hybrid Convolution Neural Network (HCNN) to construct a disease prediction system that can deal with various diseases on a single server in this paper. Physicians, radiologists, neurosurgeons, and other medical personnel will benefit from the suggested system. The accuracy predicted by this model is designed to be higher than a normal neural network. This system can also be employed to reduce the diagnostic costs and improve the accuracy of diagnosis. In countries such as India where the number of Doctor to Patient ratio happens to be 1.15 number of doctors per 1000 citizens, such models will come into a positive use as such systems improve the dependency we have on the Doctor and allows the Doctors and Healthcare workers to pay higher attention to more complicated cases. It will also improve the que time and help Doctors gain a second reliable opinion. This will in turn help in Time Management of the Doctor and Patients. Such a system is a breakthrough in such times where we are highly dependent on technology and Artificial Intelligence. There are some features which we planned to add but due to the hard time constraint were unable to integrate during the deadline. There is a plan to enable a voice agent customer chatbot which will be helping the especially abled users to make it easier for them to use the website and mobile app. The disease detection models needs to be more trained and able to diagnose a wider range of diseases. We plan on consulting a few specialized Doctors who will be able to help us make disease detection models predict more diseases and increase accuracy. For the prototype phase we have stressed on making this model hospital specific but we plan on making it offer a wider range of medical services to a range of hospitals. The most comfortable shift that Indian physicians and patients are experiencing is digitization. The internet's development, worldwide market penetration, and increased mobile phone usage are all predicted to amplify this trend. Education and awareness on the usage of digital health can help to increase the number of individuals who benefit from technology. Patients may better comprehend and engage in a discussion about their health data using digital health solutions offered on secure online web applications, which can enhance results. These technologies' data can aid providers in building a more complete picture of a person's daily health. Such platforms can really make a difference and improve the healthcare scenario in India especially in rural India where there is a problem of lack of doctors and lack of infrastructure. This is where an opportunity for such Healthcare Management Platforms shines and must be explored.

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