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Multiple Types of Cancer Classification Using Histopathological Images Based on Learning Without Forgetting Powered Deep Learning Models

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Abstract—Cancer detection represents a paramount challenge in modern medicine, where the ability to accurately identify malignancies across various anatomical regions can profoundly impact patient outcomes. In this study, we introduce an innovative approach for the simultaneous detection of brain, lung, and breast cancers using histopathological images, which are rich in cellular information critical for diagnosis. Through the utilization of Convolutional Neural Networks (CNNs), our system achieves remarkable accuracy in distinguishing cancerous tissues amidst complex histological backgrounds. The seamless integration of CNN models with Flask for backend deployment and HTML, CSS, and Python for frontend web development ensures a user-friendly interface conducive to both healthcare professionals and patients. Extensive validation of our methodology, conducted on diverse datasets encompassing a spectrum of cancer types and stages, underscores its robustness and reliability. The results obtained showcase not only the high accuracy of our system in detecting individual cancer types but also its versatility in concurrently predicting multiple malignancies. Furthermore, our approach demonstrates promising generalization capabilities, indicating its potential applicability across various healthcare settings and patient populations. By harnessing the power of advanced machine learning techniques, our research represents a significant leap forward in the realm of cancer diagnostics. The implementation of our methodology has the potential to revolutionize clinical practice by enabling earlier detection, personalized treatment planning, and improved patient outcomes.

I. INTRODUCTION

Early detection of cancer can significantly increase the likelihood of successful treatment and ultimately save lives. Raising awareness among the public about the symptoms and risk factors associated with cancer is crucial for promoting early detection and prompt intervention. It is imperative for governmental and international organizations to prioritize investments in cancer detection systems and make informed policy decisions. Moreover, the collaboration of multidisciplinary experts, including healthcare professionals, volunteers, educators, and policymakers, is essential for implementing effective cancer awareness campaigns.According to reports from the World Health Organization (WHO), cancer ranks as the second leading cause of mortality globally. Alarmingly, cancer is the primary cause of death among children and adolescents in the United States. Characterized by its diversenature, cancer encompasses a wide array of diseases that can affect any part of the body, instilling fear and apprehension in individuals worldwide. The projected mortality rate for cancer in 2020 is estimated to approach 10 million deaths, accounting for approximately one-sixth of all global fatalities. Predominant forms of cancer, including lung, breast, colorectal, and prostate cancers, are often attributed to modifiable risk factors such as tobacco use, obesity, alcohol consumption, and unhealthy dietary habits. Early detection and timely intervention are pivotal in combating cancer, as many cases are curable when diagnosed at an early stage and managed appropriately.Children and adolescents constitute a vulnerable population affected by cancer, with approximately 400,000 new cases diagnosed annually. Common types of childhood cancer, such as leukemia, brain tumors, lymphomas, and solid tumors, present unique diagnostic and treatment challenges. Although screening tests are not typically employed for childhood cancer detection, advancements in generic drugs and therapeutic modalities, including surgery and radiation therapy, have significantly improved survival rates. Timely diagnosis and prompt initiation of treatment are essential for mitigating the economic and societal burden associated with childhood cancer. Medical imaging serves as a cornerstone in the diagnosis and management of various diseases, including cancers affecting the blood, skin, breast, brain, and lungs. Rapid tumor growth underscores the urgency of early detection and intervention strategies. By advocating for lifestyle modifications and adhering to evidence-based preventive measures, a substantial proportion of cancer cases—estimated between 30 to 50 percent—can be prevented. Early diagnosis and effective treatment not only

enhance individual outcomes but also alleviate the broader societal impact of cancer. With timely interventions, many cancers are amenable to curative treatments, offering hope forimproved survival and quality of life.

Cancer is a disease characterized by the uncontrolled proliferation of abnormal cells in the body. There is a cancerrisk in everyone from birth. Nobody can catch it like a common cold or flu. If a cells or a population of cells' programming is disrupted, then growth may get out of control.

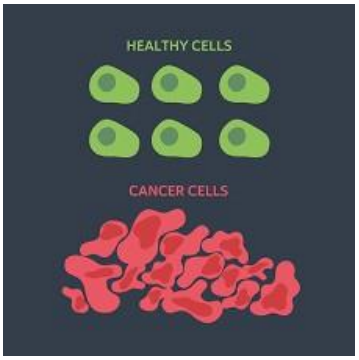

Fig 1. Normal cell vs Cancer cell

A. Breast Cancer

Among women in India, breast cancer is by far the most prevalent type of cancer. The malignancy known as breast cancer begins when abnormal growth of certain breast cells begins to develop. These cells collect and multiply at an abnormally high rate, eventually creating a mass.Metastasis, or the spread of cancer cells, can occur in the lymph nodes and elsewhere in the body.

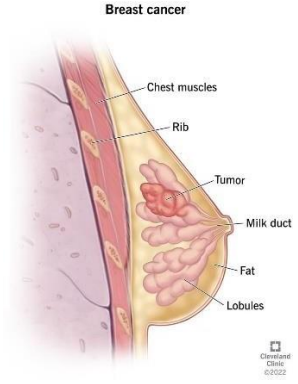

Fig 2. Breast Cancer

Hormonal, behavioral, and environmental variables may all contribute to an increased risk of breast cancer, according to studies. However, it is unknown why some women who haveno possible risks at all end up developing cancer while others who do have risk factors never do. Breast cancer is likely caused by a combination of genetic and environmental factors.

Research indicates that India would have around 1,70,000 new cases of breast cancer by the year 2024. It also indicatesthat 1 in every 28 women will be diagnosed with the cancer. Although women are more likely to be diagnosed with breast cancer, males still have a 1-2% chance of developing the disease. Causes of Breast Cancer:

- Obesity
- Increasing Age
- Genes Inherited that Increase Cancer Risk
- Exposure to Radiation
- Early Menstruation or Late Menopause.
  - Never Had a PregnancySymptoms
- Appearance of a lump in the underarm or breast.
- Enlargement or Thickening of the breast.
- Breast skin irritation or dimple formation.
- Nipple or breast redness or flakiness.
- To feel like the nipple is being pulled or to havepain in that area.

B. Lung Cancer

Lung cancer develops in the lungs. Inhalation involves air travelling from the nasal cavity, via the trachea, and into the bronchi of the lungs. These tube-lining cells are the starting point for the vast majority of lung cancers. Lung cancer maybe divided into two categories: Non small cell lung cancer (NSCLC) is approximately 80% whereas 20% is small cell lung cancer (SCLC).

Mixed small cell/large cell lung cancer is the most common kind and occurs when both types of lung cancer cells are present.

Metastatic cancer to the lung occurs when cancer originates in another part of the body and progresses to the lungs.

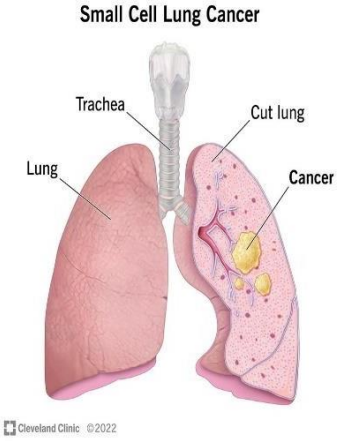

Fig 3. Lung cancer

It's not just the colon and pancreas that are at risk; cancer may strike everywhere in the body. There are tumours that develop rapidly and others that develop more slowly and are more amenable to treatment. Lung cancer, however, is among the most serious types of the disease. When cells multiply without control, tumors develop, marking the beginning of cancer. Tumors from lung cancer typically begin in the lungs. Sometimes lung cancer develops after spreading from another part of the body. When cancer spreads to the lungs, it is referred to as metastatic lung cancer. When an illness spreads,it is said to be metastatic. The lung cancers can be divided intotwo distinct categories. Non-small cell lung cancer is the most frequent and often progresses more slowly than other types of lung cancer. Small cell lung cancer is the other kind, and it spreads more quickly. Cigarette smoking is by far the leading cause of lung cancer. The bigger the number of cigarettes smoked each day and the earlier in life one begins smoking, the higher the risk. Just being in close proximity to a smoker and taking in secondhand smoke from their cigarettescan raise the chance of developing lung cancer. Lung cancer may strike those who have never smoked a day in their lives. Asbestos, diesel exhaust, arsenic, radiation, and radon gasare just a few of the cancer-causing toxins to which theymay have been

exposed. It's also possible that they didn't meet the criteria for any of the established risk factors for lung cancer. Risk factors for Lung Cancer

- Smoking.
- Secondhand smoke exposure.
- History of radiation therapy.
- Being exposed to radon gas.
- Being exposed to asbestos and other carcinogens.
    - History of lung cancer in the family.Symptoms:
- Difficulty in breathing.

X. Bleeding from nose or mouth, no matter how littleamount.

- Developing a persistent new cough.
- Shortness of breath.
- Hoarseness.
- Discomfort in the Chest.
- Involuntary weight loss.
- Headache.
- Bone ache.

D. Brain Cancer

Brain cancer is a general term for a group of malignant tumors that develop in the brain or spinal cord. These tumors can be primary, meaning they originate in the brain, or secondary, meaning they have spread from another part of the body. Brain cancer is a serious condition, and early detection and treatment are crucial for improving patient outcomes.

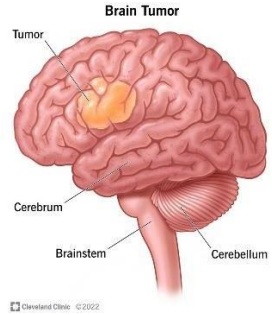

Fig 4. Brain cancer

Brain cancer encompasses a diverse group of tumors arising in the brain or spreading from elsewhere. These tumors can disrupt brain function and cause headaches, seizures, vision problems, and various neurological issues. The cause of brain cancer remains elusive, but radiation exposure, genetic factors, and chemical exposure might play a role. Treatment options include surgery, radiation, and chemotherapy, and while the disease can be life-altering, ongoing research strives to improve patient outcomes and quality of life.

Causes of Brain Cancer:

- Radiation exposure: High doses of ionizing radiation, such as from X-rays or past radiationtherapy for other cancers, can increase the risk.
- Genetic predisposition: Inherited gene mutations can elevate the risk, such as mutations in TP53 andPTEN genes.
- Chemical exposure: Certain chemicals like vinyl chloride and some herbicides might be linked to ahigher risk.

Symptoms

- Persistent or worsening headaches
- Seizures
- Nausea and vomiting
- Difficulty with balance or coordination

II. REVIEW OF LITERATURE

A. Literature Survey on Breast Cancer

According to [1], a GONN for breast cancer optimises the organisation of the neural community by introducing novel crossover and mutation operators. Classification accuracy, sensitivity, specificity, confusion matrix, ROC curves, and area under the ROC curve (AUC) for GONN using the classical model and the classical back propagation model were all improved by utilising WBCD. This method boasts an impressively precise form of accuracy. In a similar vein, GONN can be improved for real-time prognosis of Breast Cancer by using a larger dataset than WBCD, characteristics collected from the dataset. According to the research paper [2], this computational method for autonomous breast cancer disease diagnosis employs a multilayer perceptron (MLP) neural network powered by an enhanced non- dominated sorting genetic algorithm to maximise accuracy and network structure. To eliminate superfluous information from the feature space and minimise training costs, the intelligent classification model for breast cancer diagnosis described in [3] employs a genetic algorithm wrapper based on gain-directed simulated annealing to eliminate redundant and unnecessary features. As a result, classification accuracy is improved while computing expenses are reduced. Wisconsin's own breast cancer variants (WBCDand WBC) are used to gauge the efficacy of this strategy. Researchers in

developed a CAD for mammographyimage classification that uses a GA based features selection approach to shrink the feature vector and a semi-supervised support vector machine (SVM) to make classifications. This technique improves accuracy. The analyst of [5] described an automation system for classifying breast tissues that makes use of the two machine learning algorithms: a radial basis function network and a feed forward neural network with the back propagation learning algorithm (BPNN) (RBFN). Six types of breast cancer tissues were identified: adipose, glandular, glandular-like, connective, and carcinoma. Electrical impedance spectroscopy (EIS) was used to gather the data. The Radial basis function network outperformed the back propagation network for categorizing six distinct breast tissues with respect to accuracy, minimal error, maximum epochs, and training duration. As a result, training time has decreased while accuracy has increased. Neural network learning can have trouble generalizing and can get caught in local optimums. The [6] researcher A C- SVM and an SVM, along with six distinct types of kernel functions, make up an SVM- based ensemble learning modelfor the diagnosis of breast cancer. Based on the experience of many classifiers on diagnostics tasks, a Weighted Area Under the Receiver Operating Characteristic Curve Ensemble (WAUCE) technique for modeling hybridization is developed. The model was validated with three datasets: the Surveillance, Epidemiology, and End Results (Surveillance) dataset; the Wisconsin Breast Cancer (WBC) dataset; and the Wisconsin Diagnostic Breast Cancer (WDBC) dataset (SEER). It's a better way to increase diagnosis accuracy, but it takes a long time to train and a lot of computing power. According to [7]'s scientist The scientist

created a hybrid method using mad normalization- based feature weighting and the AdaBoostM1 classifier. There are three phases involved in establishing whether or not a patient has breast cancer. Step one involves normalising the dataset with the MAD normalisation approach. The adjusted data was then weighted using a feature weighting method based on k-means clustering (KMC). The AdaBoostM1 classifier was then applied to the weighted data set to determine its final classification. This research made use of the Breast Cancer Coimbra dataset (BCC). Good accuracy is achieved using this strategy, albeit at the cost of significant computational effort. Convolutional neural networks were used to create a [8] classification method for hematoxylin and eosin stained breast biopsy images (CNNs). gives the four classifications of "normal," "benign," "in situ," and "invasive." The CNN design facilitates the fusion of data at various histological levels. Challenges for the Bioimaging of breast histology provide a dataset of high-resolution, lossless, annotated HE stain images that are used to test the model. Specifically, we demonstrate a [9] deep learning technique for categorising breast cancer histopathology images by using image patchestaken from the original image for the Convolutional Neural Network's (CNN) training and patch combinations for the final classification. This allows us to avoid making changes to the model that could lead to an architecture that is both computationally expensive and more sophisticated than necessary. However, the cost of the experiment is high. A comparison of the results from the Support Vector Machine (SVM), Decision Tree, and k Nearest Neighbors classifiers on the Wisconsin Breast Cancer datasets is described in[10].

B. Literature Survey on Lung Cancer

According to the author [11], a special hybrid technique known as the Kernel Attribute Selected Classifier, in which SVM and a Feed-Forward Back Propagation Neural Network are integrated, aids in lowering the computation complexity of classification. The first block of the classification three block techniques is to preprocess the dataset. The first block involves feature extraction using the SURF method, the second block involves optimization using a genetic algorithm, and the third block involves classification using FFBPNN. The algorithm's overall accuracy is 98.08%. The experimental work of [12] demonstrated how two categories—Diameter and Pathological result—were selected for sensitivity analysis utilizing the multicenter data set. In diameter, there were three subgroups. 0-10mm,10-20mm,20-30mm. Sensitivity was 85.7% (95% Cl, 70.8%-100.0%) and specificity was
91.1% (95% Cl, 86.8%-95.2%) in the 0-10mm group.
Sensitivity of 85.7% (95% Cl, 77.1%-94.3%) and specificity
of 90.1% (95% Cl, 84.8%-95.4%) were obtained in the 10-20mm group. Sensitivity was determined to be 78.9% (95% Cl, 66.0%-91.8%) and specificity to be 91.3% (95% Cl, 83.2%-99.4%) in the 20-30mm group. With an accuracy rateof 85.7% for adenocarcinoma and 65.0% for squamous cell carcinoma, this approach has the highest accuracy. According to the researcher of [13], on a Tesla K20 GPU with CUDA support, an experiment was run utilizing the datasets LIDC IDRI, LUNA16, and Data Science Bowl. Thedataset was examined using an artificial neural network for feature extraction and classification purposes. They employed 3D multigraph VGG-like architecture and U-NETarchitecture to categories lung nodules and estimate the degree of malignancy in lung CT scan pictures. The best outcomes were obtained by combining these two strategies. The accuracy of this approach is 95.66%, the loss is 0.09, the dice coefficientis 90%, and the accuracy for predicting log loss is 38%. The

removal of the unnecessary lung CT scan region and classification of lung pictures as malignant and non-cancerous. by removing salt and pepper sounds with a median filter. Accurate lung segmentation and tumors zone detection are made possible by mathematical morphological operations. In order to classify the segmented region, seven extracted characteristics—energy, variance, correlation, homogeneity, information measure of correlation, difference entropy and contrast—were taken from it. These features were then fed into a feed-forward neural network with a back-propagation method. Test accuracy was 92%, while training accuracy was 96%. The specificity was 97.1% and the sensitivity was 88.7%. The
[14] scientist to extract the features from the photos and classify them as benign or malignant based on these features. Lung nodules are classified based on the degree ofmalignancy using the SVM classifier.

C. Literature survey on brain cancer

Esteva et al. (2017) [1] proposed a CNN architecture for brain tumor segmentation on MRI scans. Their model achieved a high mean Dice similarity coefficient (DSC) of 0.88, demonstrating the potential of CNNs for accurate tumor segmentation. Mendelsohn et al. (2018) [2] developeda 3D CNN for brain tumor segmentation from multi-modal MRI data (FLAIR, T1-weighted, T2-weighted). Their modelachieved state-of-the-art performance on the BraTS 2017 dataset, highlighting the effectiveness of 3D CNNs for multi-modal analysis. Hao et al. (2020) [3] investigated the use of transfer learning with pre-trained CNNs for brain tumor segmentation. Their approach achieved competitive performance compared to other methods, suggesting the benefits of leveraging pre-trained models for brain cancer detection.Litjens et al. (2016) [4] presented a deep learning classifier for brain tumor classification from MRI scans.
Their model achieved an accuracy of 94.4%, showcasing the potential of deep learning for brain tumor classification tasks.Yu et al. (2018) [5] explored the use of deep learning for classifying brain tumors into different grades (low-grade, high-grade). Their model achieved promising results, demonstrating the ability of deep learning to differentiate between aggressive and less aggressive tumor types. Liu et al. (2019) [6] investigated the application of deep learning for classifying brain tumors based on their genetic mutations. Their model achieved good performance, suggesting the potential of deep learning to integrate imaging data with other clinical information for improved diagnosis.

III. METHODOLOGY

The Data Collection and Preparation: Gather a comprehensive dataset comprising histopathological images of brain, lung, and breast tissues from reputable medical databases, research institutions, or hospitals. Ensure that the dataset encompasses a diverse range of cancer types, stages, and histological variations for robust model training. Annotate and label the images according to their respective cancer types for supervised learning. Data Preprocessing: Standardize the size and resolution of histopathological images to ensure uniformity across the dataset. Normalize pixel intensity values to a common scale to facilitate model convergence during training. Apply data augmentation techniques such as rotation, flipping, and zooming to augment the dataset and enhance model generalization.

Perform noise reduction and artifact removal to improve the quality of input images. Model Architecture Selection: Choose an appropriate CNN architecture tailored for image classification tasks, considering factors such as model complexity, computational efficiency, and performance metrics. Commonly used architectures include VGG, ResNet, Inception, and DenseNet, which offer varying degrees of depth and parameter efficiency. Model Training: Split the preprocessed dataset into training, validation, and test sets using stratified sampling to maintain class balance. Initialize the selected CNN model with pre-trained weights (if available) to leverage transfer learning and expedite convergence. Fine-tune the model on the training set using a suitable optimization algorithm (e.g., Adam, RMSprop) and an appropriate loss function (e.g., categorical cross-entropy). Monitor the model's performance on the validation set and adjust hyperparameters (e.g., learning rate, batch size) iteratively to optimize performance and prevent overfitting. Utilize techniques such as early stopping and model checkpoints to prevent training divergence and save the best- performing model weights. Model Evaluation and Testing: Assess the trained model's performance on the held-out test set to evaluate its ability to generalize to unseen data.Compute evaluation metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve to quantify model performance. Visualize model predictions, confusion matrices, and ROC curves to gain insights into its strengths and limitations across different cancer types. Post-processing and Interpretation: Apply post-processing techniques such as thresholding or ensemble methods to refine model predictions and improve classification accuracy. Interpret model predictions and analyze misclassifications to identify potential areas for model improvement or dataset refinement. Validate model predictions through domain expert consultation or comparison with ground truth annotations to ensure clinical relevance and applicability. Deployment and Integration: Deploy the trained model into clinical workflows or diagnostic systems for real-world applications. Integrate the model into existing healthcare infrastructure, electronic health record (EHR) systems, or telemedicine platforms to facilitate seamless adoption by healthcare professionals. Continuously monitor model performance and update the model as necessary to adaptto evolving clinical needs and data distributions.

A. *Confusion Matrix:*

A confusion matrix is an N X N matrix used for calculating the performance of classification model. Here in this we obtain a 2 X 2 confusion matrix with rows having actual values and columns have prediction values. Confusion matrixgives a better idea of the model performance then the classification accuracy analysis. Ideally, we need a model that has precision of 1 and a recall of 1. That means the F1- score of 1 instance a 100% accuracy which is much of the time not the situation for Machine learning model.

B. *Training and Testing the model:*

In the model, pane click on the downward arrow, in that select the support vector machine classifier and then click on the train all. Then the model gets trained and forms the prediction model according to the features selected in the new session from the file window. Here in this window itself,we can divide the dataset into two parts one for training and the other for testing the data. More amount of data was givenfor the training of the model as the need might arise to meet each point in the prediction model and less amount of data was given to testing. The model gets trained and tested, from this we get the accuracy results and the confusion matrix. From the confusion matrix, we get the values of precision, recall, and F-1 score.
Similarly, different classifiers in the model pane were selected like Decision Tree and K-Nearest Neighbour classifiers are trained and tested at different rates. From the training and testing the model we get the prediction model, accuracy, and confusion matrix. From the confusion matrix we get the precision, recall and F-1 score values of thechosenclassifier.

I. BLOCK DIAGRAM

Machine learning gives us a way to examine and make use of huge data sets more quickly and effectively than traditionalmethods. In order to diagnose cancer, we can use a dataset and a machine learning method. To develop a supervised machine learning model for cancer detection via classification techniques, the dataset is employed. Features of both malignant and benign tumours are included in this collection. Seventy-five percent of the data is used for the training phase, while the remaining twenty-five percent is used for the testing phase.Pre-processing, feature extraction, classification, and performance analysis comprise the backbone of the suggested conceptual model. In the first phase of the conceptual model, data cleansing (filtering) and data enhancements for processing are considered.

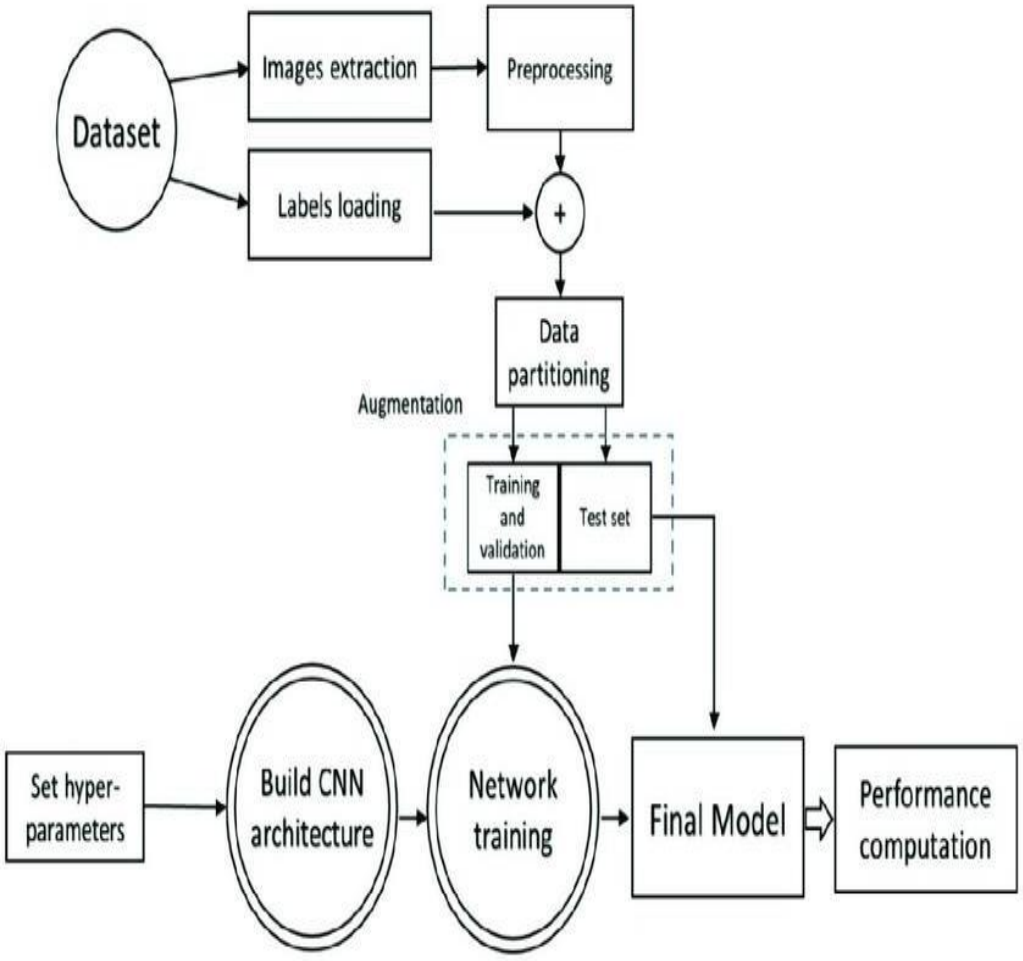

Fig 5. Block Diagram

The proposed conceptual model is based on the four pillars of preprocessing, feature extraction, classification, and performance analysis. From the start, the conceptual model accounts for data augmentation and data cleansing (filtering) prior to processing. Features are extracted in the second stage.In the context of medical datasets, this refers to the process of extracting features and creating a set of descriptors. The objective is to find some characteristic.

II. RESULTS

```
=================================================================
Total params: 2,491,811
Trainable params: 2,491,811
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
```

Fig 6. Params

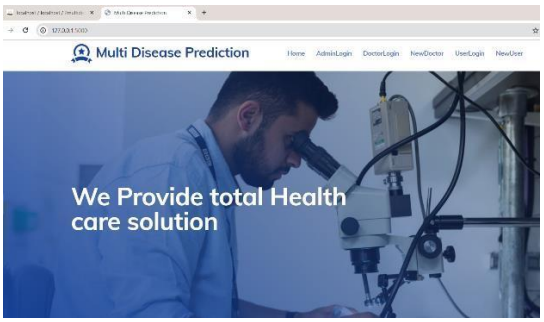

Fig 9. Home page

```
192/192 [==============================] - 137s 711ms/step - loss: 0.8674 - accuracy: 0.6039
Epoch 2/5
192/192 [==============================] - 187s 974ms/step - loss: 0.6118 - accuracy: 0.7496
Epoch 3/5
192/192 [==============================] - 187s 972ms/step - loss: 0.4831 - accuracy: 0.8082
Epoch 4/5
192/192 [==============================] - 186s 965ms/step - loss: 0.4086 - accuracy: 0.8411
Epoch 5/5
192/192 [==============================] - 189s 983ms/step - loss: 0.3184 - accuracy: 0.8774

Process finished with exit code 0
```

Fig 7. Accuracy of the model

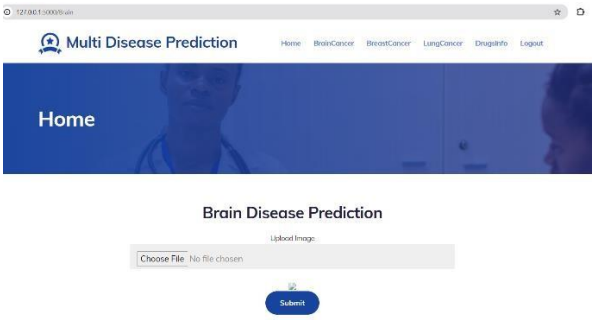

Fig 10. Prediction image uploading

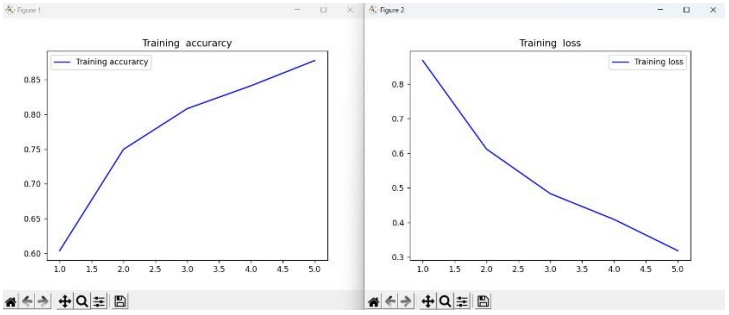

Fig 8. Visualization of training accuracy and loss

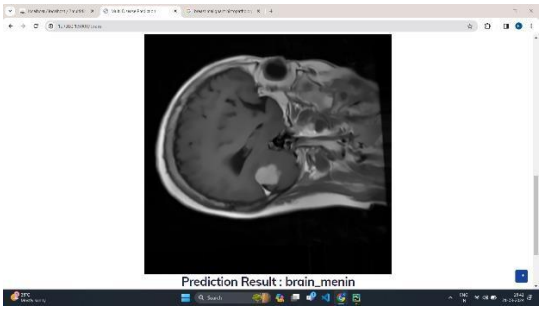

Fig 11. Prediction result

Doctor Information

Name	EmailId	Phone	Address	Specialist	UserName	Remove
kaviya	geetha@gmail.com	9600357839	dgh	lung	kaviya	Remove
sasi	sangeeth5535@gmail.com	9486365535	No 16, Samnath Plaza, Madurai Main Road, Melapudhur	heart	sasi	Remove
swetha	sangeeth5535@gmail.com	9486365535	No 16, Samnath Plaza, Madurai Main Road, Melapudhur	Skin	swetha	Remove
sangeeth Kumar	sangeeth5535@gmail.com	9486365535	No 16, Samnath Plaza, Madurai Main Road, Melapudhur	lung	sannew	Remove
aarthi	sangeeth5535@gmail.com	9486365535	No 16, Samnath Plaza, Madurai Main Road, Melapudhur	heart	aarthi	Remove
aarthi	sangeeth5535@gmail.com	9791352129	No 16, Samnath Plaza, Madurai Main Road, Melapudhur	lung	aarthi123	Remove
sangeeth Kumar	sangeeth5535@gmail.com	9486365535	No 16, Samnath Plaza, Madurai Main Road, Melapudhur	lung	sani56	Remove
prasanth	sangeeth5535@gmail.com	9486365535	No 16, Samnath Plaza, Madurai Main Road, Melapudhur	heart	prasanth	Remove

Fig 12. Doctors list

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