AI – POWERED BIOMEDICAL IMAGE ANALYSIS

Internal Guide:

Dr. P. Subhashini

Professor

BY:

20R21A3321 – K. KAVYASRI

ABSTRACT

Biomedical image analysis plays a crucial role in the early and accurate diagnosis of diseases, significantly impacting patient outcomes. This study presents an innovative approach to biomedical image analysis by integrating machine learning techniques with a user-friendly web interface. The system takes input images uploaded through the web interface and processes them using advanced machine learning algorithms implemented in Python. The goal is to automate the detection of diseases from these images, enhancing the efficiency and precision of diagnosis.

LITERATURE SURVEY

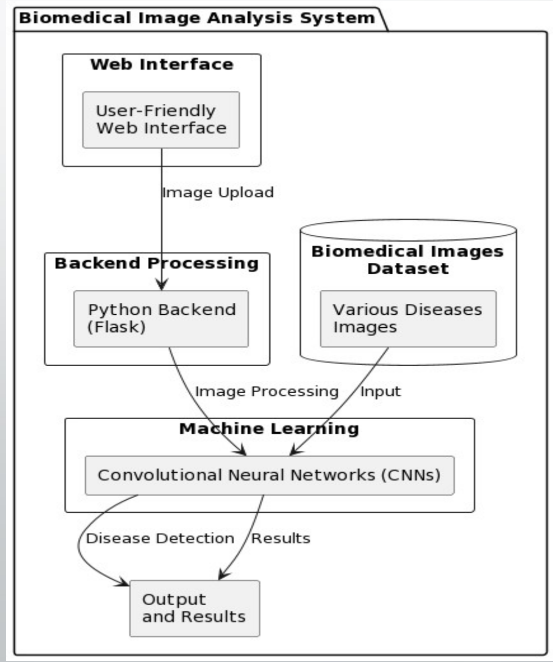
S.NO	TITLE & AUTHOR	DESCRIPTION	PROS	CONS
1	AI and Medical Imaging Informatics: Current Challenges and Future Directions A. S. Panayides, Senior Member, IEEE, A. Amini, Fellow, IEEE	This paper provides an in-depth examination of AI in Medical Imaging Informatics, covering current challenges, future directions, and the importance of global collaboration and ethical considerations.	1. Comprehensive coverage of current challenges and future directions in AI integration with Medical Imaging Informatics. 2. Detailed exploration of challenges like data quality and privacy concerns, demonstrating a nuanced understanding.	1. Information may become quickly outdated due to the evolving nature of technology and healthcare. 2. Lack of regular updates to maintain relevance may affect the usability of the resource over time.
2	A Systematic Literature Review of Medical Image Analysis Using Deep Learning; ; ;	The paper explores the application of Deep Learning in Medical Image Analysis, focusing on cancer tissue identification, lung pattern classification, and brain tissue segmentation for improved diagnosis and treatment outcomes.	1. Comprehensive overview of current research. 2. Consolidates knowledge for researchers.	1. May lag behind latest developments. 2. Scope limitations and potential bias.
3	Deep Learning Applications in Medical Image Analysis; ; ;	The paper provides an in-depth exploration of Convolutional Neural Networks (CNNs) and their applications in medical image analysis, emphasizing their ability to preserve spatial relationships and classify images with high accuracy.	1. CNNs preserve spatial relationships, enhancing accuracy in medical image analysis. 2. The architecture enables precise feature extraction and classification.	1. Demands significant computational resources. 2. Interpretability challenges and potential loss of fine details in pooling operations.

Year - [REF] Author	Disease	Imaging Data	Patients	DL Method	Segmentation/ Classification	Description
1995 - [100] Lo et *al*	Lung Cancer	X-ray	55	2 layer CNN	Nodules detection in a patch fashion	First ever attempt to use CNN for medical image analysis
2015 - [104] Ronneberger et *al*	Cells	Electron and optical microscopy	30 /35	U-net	Segmentation of EM images and cell tracking	Image to image tasks architecture depicting exceptional segmentation performance even with limited data
2016 - [118] Shin et *al*	Interstitial Lung Disease	CT	120 (905 slices)	Transfer learning (AlexNet, GoogleNet, CifarNet CNNs)	Interstitial lung disease binary classification	Showed that networks pre-trained on natural image data could be succesfully used on medical data
2016 - [122] Dou et *al*	Cerebral Microbleeds	MRI	320	Two-stage: 1) 3D Fully-convolutional network (FCN), 2) 3D CNN	3D FCN for candidate microbleed detection	A two-stage system used a 3D FCN to detect candidate microbleeds before a 3D CNN was applied to reduce false positives
2016 - [127] Setio *et al*	Pulmonary Cancer	CT	888 scans, 1186 nodules	Two-stage: 1) Feature-engineered candidate detector, 2) Multi-view 2D CNN for false positive reduction	Candidate pulmonary nodules detection	Significantly reduced false positives using fusion of multiple 2D CNNs at different views around a nodule
2017 - [268] Lekadir et *al*	Cardiovascular (carotid artery)	US	56 cases	Four convolutional and three fully connected layers	Characterization of carotid plaque composition	High correlation (0.90) with plaque composition clinical assessment for the estimation of lipid core, fibrous cap, and calcified tissue areas
2017 – [128] Yu et *al*	Melanoma	Dermoscopic Images	1250 images	Very deep (38/50/101 layers) fully conv. residual network	Binary melanoma classification	Used a very deep residual network (16 residual blocks) to classify melanoma
2017 - [102] Komnitsas et *al*	TBI, LGG/ GBM, Stroke	MRI	61 /110/ ISLES-SISS data	11-layers, multi-scale 3D CNN with fully connected CRF	Brain lesion segmentation algorithm	Top-performing segmentation results on TBI, brain tumours, and ischemic stroke at BRATS and ISLES 2015 challenges
2017 - [246] Lao et *al*	GBM	MRI	112	Transfer learning	Necrosis, enhancement, and edema tumour subregions	Overall survival prognostic signature for patients with Glioblastoma Multiforme (GBM)
2017 - [247] Oakden-Rayner et *al*	Overall Survival	CT (chest)	48	ConvNet transfer learning (3 convolutional and 1 fully connected layers)	Tissue (muscle, body fat, aorta, vertebral column, epicardial fat, heart, lungs)	Predict patients' 5-year mortality probability using radiogenomics data (overall survival)
2017 - [241] Zhu et *al*	Breast Cancer	DCE-MRI	270	Transfer learning (GoogleNet, VGGNet, CIFAR)	Breast tumour lesions	Discriminate between Luminal A and other breast cancer subtypes
2018 - [112] Chartsias et *al*	Cardiovascular	MRI	100	Various networks	Segmentation of cardiac anatomy	Limited training data when appropriate autonecoding losses are introduced
2020 – [121] McKinney et *al*	Breast Cancer	X-ray	25,856 & 3,097 cases	Ensemble and transfer learning	Breast cancer classification	Cancer prediction on two large datasets with comparison against human readers
2019 - [170] Hekler et *al*	Melanoma	Whole slide H&E tissue imaging	695	Transfer learning (ResNet50)	Binary melanoma classification	Human level performance in discriminating between nevi and melanoma images

US: Ultrasound; MRI: Magnetic Resonance Imaging; DCE-MRI: Dynamic Contrast Enhancement MRI; CT: Computed Tomography; PET: Positron Emission Tomography; GBM: Glioblastoma; LGG: Lower-Grade Glioma; CNN: Convolutional Neural Networks.

PROPOSED SYSTEM

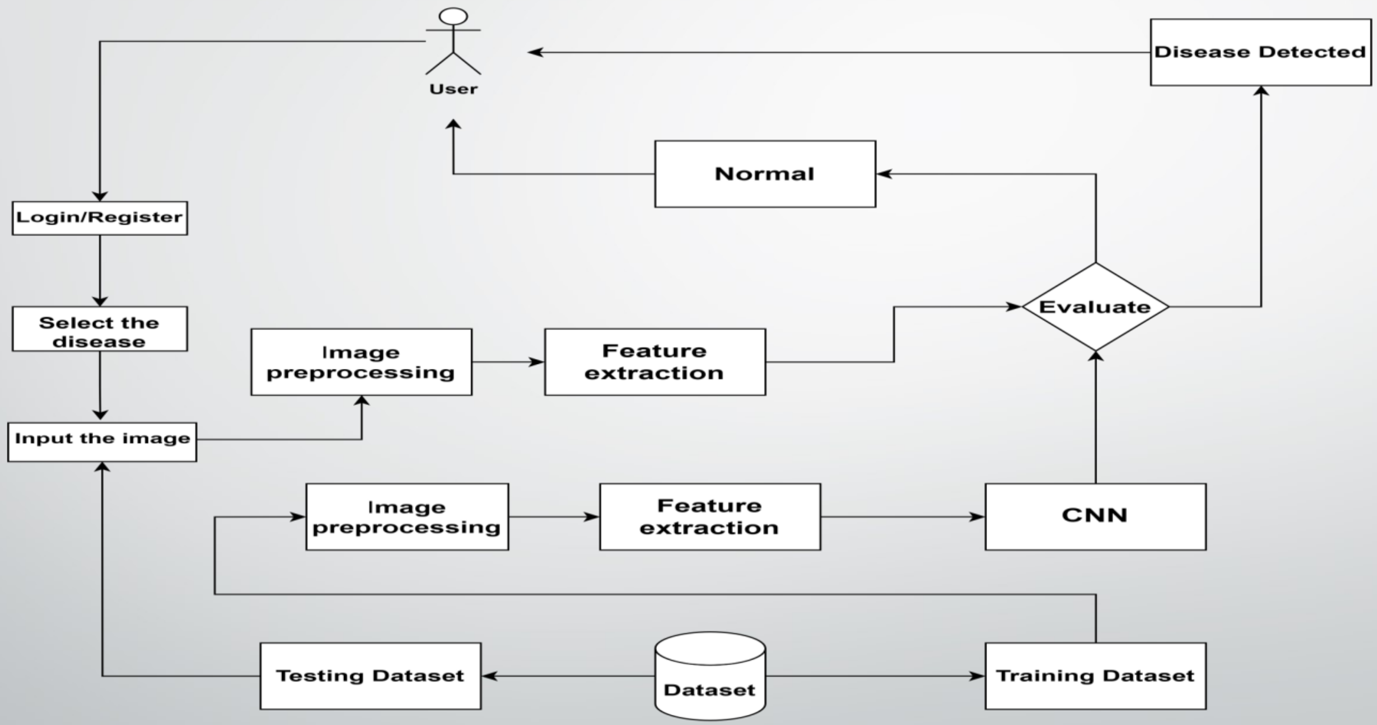
- The proposed system architecture establishes a user-centric experience by seamlessly incorporating a web interface, facilitating the effortless uploading of images for healthcare professionals and users alike. comprises several interconnected modules to automate disease detection and classification from uploaded biomedical images.



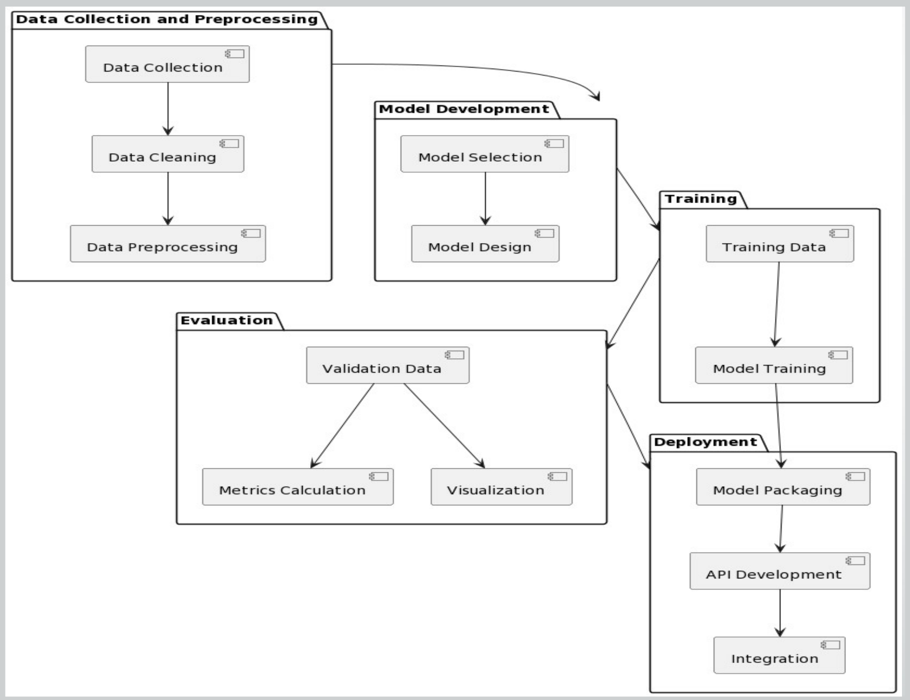
The proposed system modules are:

- Data Collection and Preprocessing
- Model Development
- Training
- Evaluation
- Deployment

PROPOSED SYSTEM ARCHITECTURE



MODULE DIVISION



The proposed system comprises several interconnected modules designed to streamline the process of biomedical image analysis using artificial intelligence and machine learning techniques. Each module plays a critical role in different stages of the system's workflow, ensuring the efficient collection, processing, training, evaluation, deployment of machine learning models for disease detection.

DATA COLLECTION AND PREPROCESSING

This module is responsible for gathering and preparing the biomedical image data required for training and testing the machine learning models.

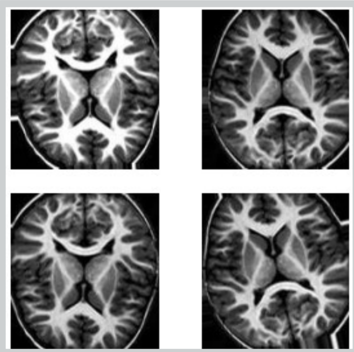
Data Collection

In this phase, a diverse range of biomedical images is gathered from multiple sources such as medical databases, research institutions, or hospitals. These images may include X-rays, MRI scans, CT scans, histopathological slides, and more, covering various diseases and conditions. Ensuring a diverse dataset is crucial for training a robust and generalizable machine learning model.

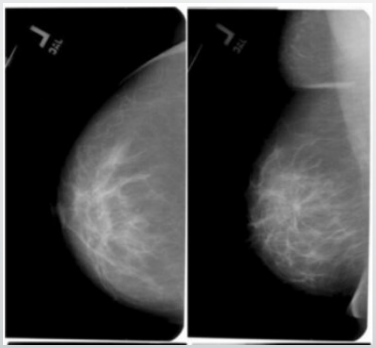
Data Cleaning Data collected from different sources may contain inconsistencies, errors, or artifacts that could adversely affect model training. Data cleaning involves preprocessing steps such as removing duplicate images, correcting mislabelled data, and addressing any noise or artifacts present in the images.

DATASETS

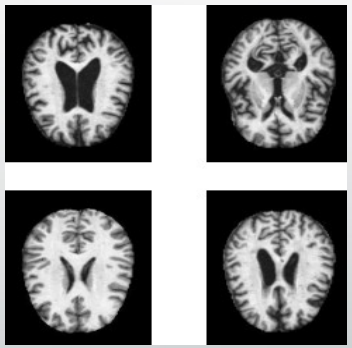
Our project's success hinges on the quality and diversity of the datasets we've curated and utilized. Across five distinct categories of diseases – Brain Tumor, Breast Cancer, Alzheimer's, Pneumonia, and Heart Disease – we've amassed a rich repository of medical images. Each dataset offers a unique glimpse into the complexities of diagnosing and treating these ailments, with varying numbers of images reflecting the prevalence and importance of each condition.



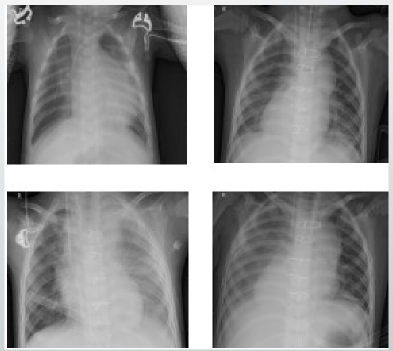
Brain Tumor



Breast Cancer



Alzheimer



Pneumonia

Heart Disease

MODEL DEVELOPMENT

In this module, the appropriate machine learning or deep learning model architecture is selected and designed based on the requirements and characteristics of the biomedical image analysis task.

Model Selection involves evaluating different model architectures and selecting the most suitable one based on factors such as performance, complexity, and interpretability.

Model Architecture Design defines the structure and configuration of the chosen model, including the number of layers, types of activation functions, and connectivity patterns.

TRAINING

This module focuses on training the selected model using the prepared dataset to learn patterns and features from the biomedical images.

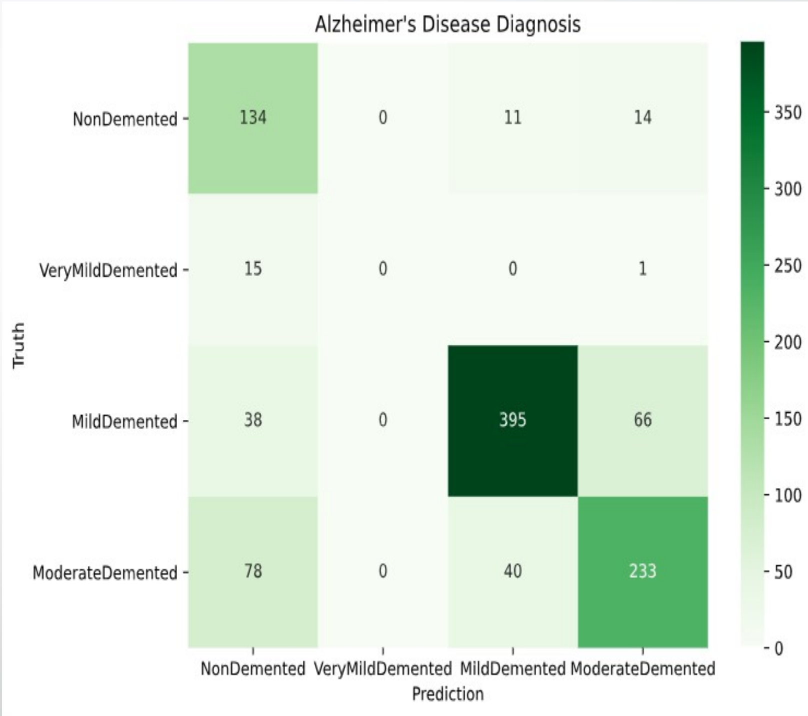
Training Data prepares the dataset for training by splitting it into training, validation, and test sets, ensuring proper evaluation of the model's performance.

Model Training involves feeding the training data into the selected model and iteratively adjusting its parameters to minimize the prediction error.

EVALUATION

After training, this module evaluates the performance of the trained model using separate validation and test datasets.

Validation Data assesses the model's performance on unseen data to ensure its generalization ability and prevent overfitting.
Metrics Calculation computes various evaluation metrics, such as accuracy, precision, recall, and F1 score, to quantify the model's performance objectively.
Visualization generates visual representations of the model's predictions and performance metrics to aid in understanding and interpretation.



DEPLOYMENT

Once the model is trained and evaluated, this module packages and deploys it into a production environment for real-world usage.

Model Packaging: Involves converting the trained machine learning model into a deployable format, such as TensorFlow SavedModel ensuring compatibility with the target deployment environment.

API Development: Creates an application programming interface (API) that exposes the functionality of the deployed model to external systems or applications.

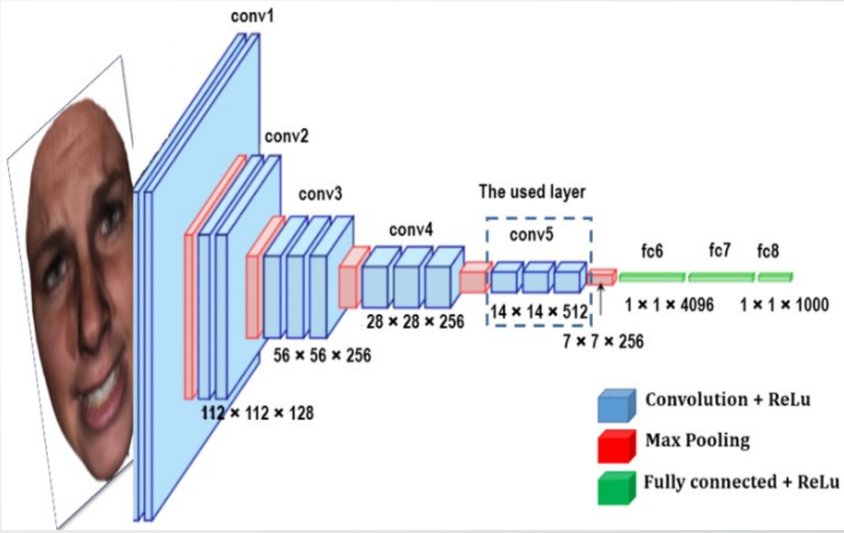
Integration: Involves seamlessly integrating the deployed model into the production environment, ensuring its interoperability with existing systems, databases, or workflows.

ALGORITHM

In the proposed project, Convolutional Neural Networks (CNNs) serve as the primary algorithm for biomedical image analysis. CNNs are a class of deep learning models specifically designed for image recognition and classification tasks.
CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply convolutional filters to the input image, extracting various features such as edges, textures, and shapes. Pooling layers then downsample the feature maps, reducing their spatial dimensions while preserving important information. Finally, fully connected layers integrate the extracted features to make predictions or classifications.

ALGORITHM

In this CNN architecture we have used VGG 16 model to train the dataset . The VGG-16 model is a convolutional neural network (CNN) architecture that was proposed by the Visual Geometry Group (VGG) at the University of Oxford. It is characterized by its depth, consisting of 16 layers, including 13 convolutional layers and 3 fully connected layers. VGG-16 is renowned for its simplicity and effectiveness, as well as its ability to achieve strong performance on various computer vision tasks, including image classification and object recognition.



DATASET ANALYSIS

The AI-powered biomedical image analysis system relies on comprehensive datasets comprising various biomedical images depicting different diseases and conditions. These datasets are essential for training and evaluating the performance of the machine learning models, particularly Convolutional Neural Networks (CNNs). The datasets are carefully curated to encompass a wide range of medical conditions.

We used different datasets for each disease. The diseases are Brain Tumor, Breast Cancer, Alzheimer, Pneumonia, Heart Disease. The given table depicts the dataset of each disease. We took 80% of data for training and 20% of data for testing.

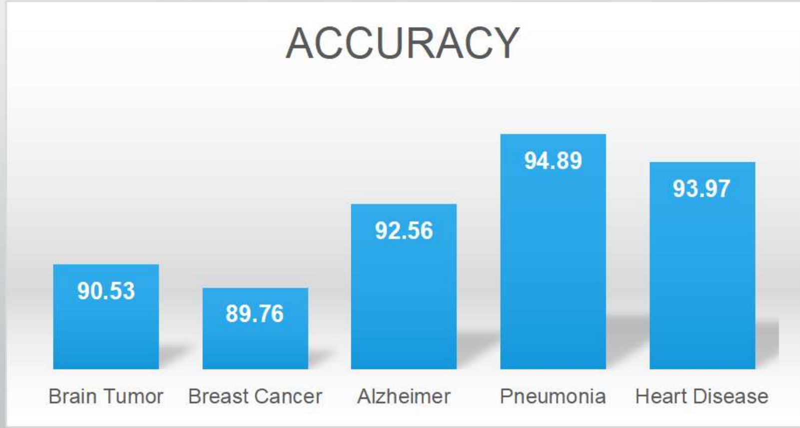
DISEASE DATASET	NO. OF IMAGES	TRAIN	TEST
Brain Tumor	291	233	58
Breast Cancer	570	456	114
Alzheimer	6400	5120	1280
Pneumonia	6270	5226	1045
Heart Disease	304	243	61

RESULT ANALYSIS

The accuracy of each dataset obtained through Convolutional Neural Networks (CNNs) reflects the system's capability to precisely classify biomedical images, contributing to the early and accurate diagnosis of diseases. Through rigorous training and evaluation processes, the CNN-based model achieves notable accuracies, demonstrating its proficiency in distinguishing between different medical conditions depicted in the datasets.

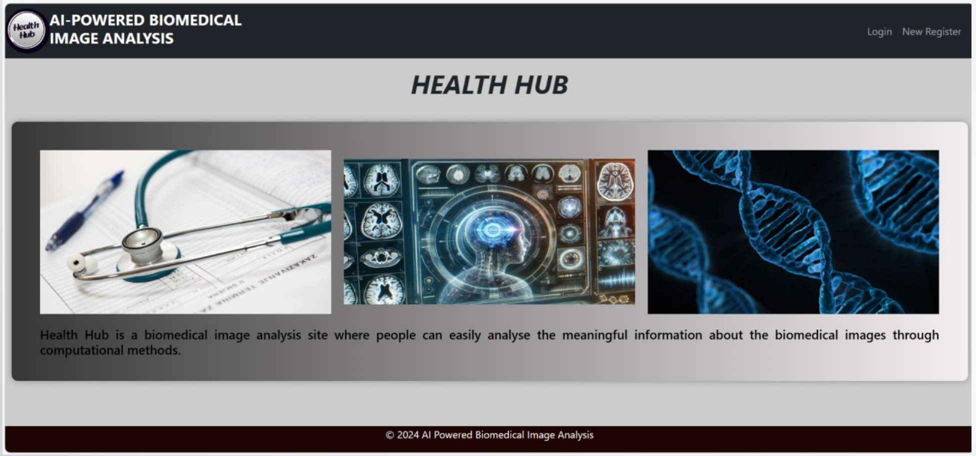
$$\text{Accuracy} = \frac{\text{Predicted images}}{\text{Total no.of images}}$$

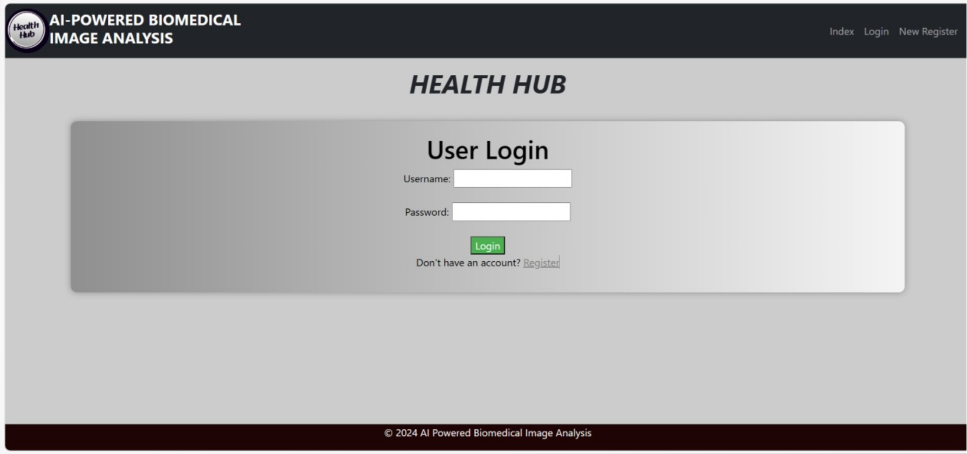
DISEASE DATASET	ACCURACY
Brain Tumor	90.53
Breast Cancer	89.76
Alzheimer	92.56
Pneumonia	94.89
Heart Disease	93.97

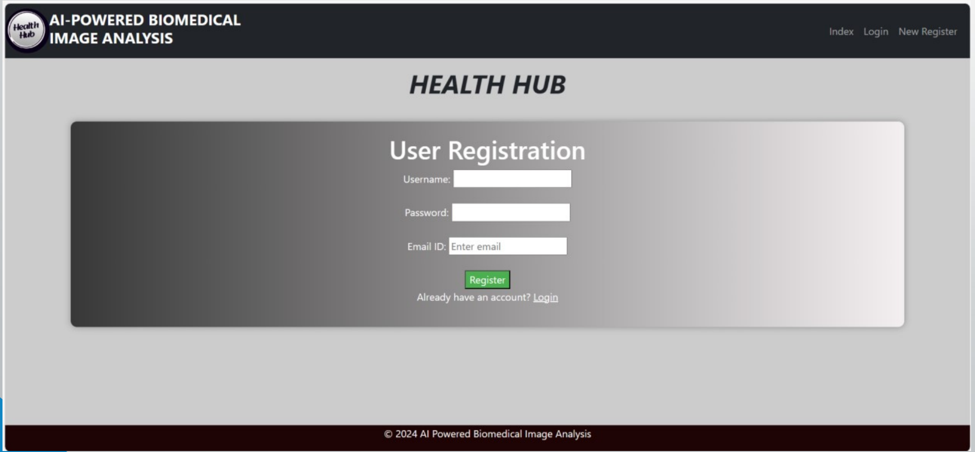


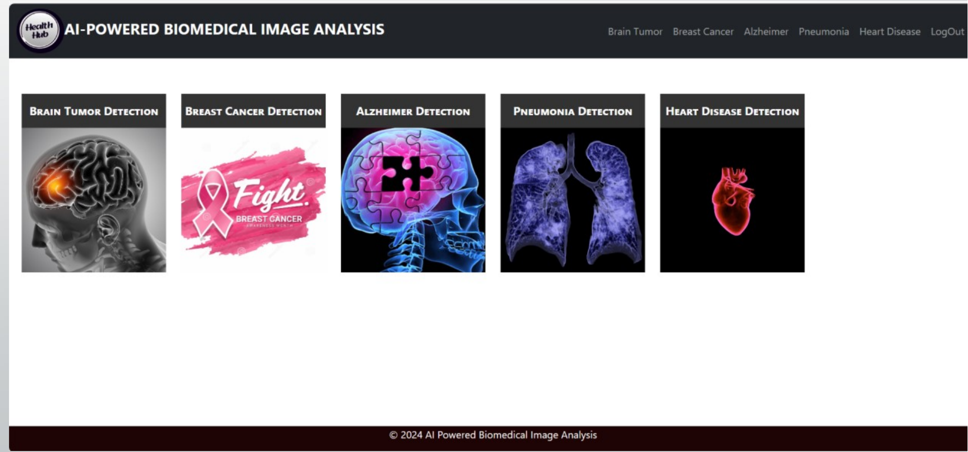
MLRIT
Raising Engineers
MLR INSTITUTE OF TECHNOLOGY

RESULT

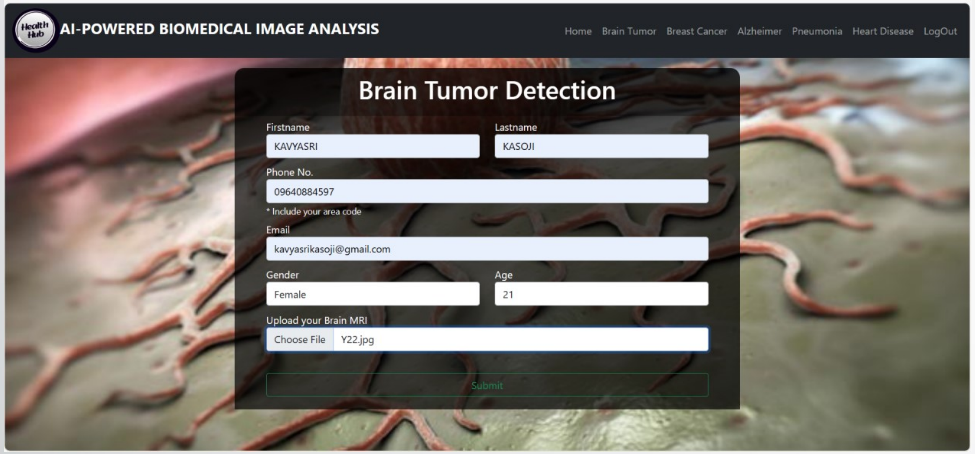


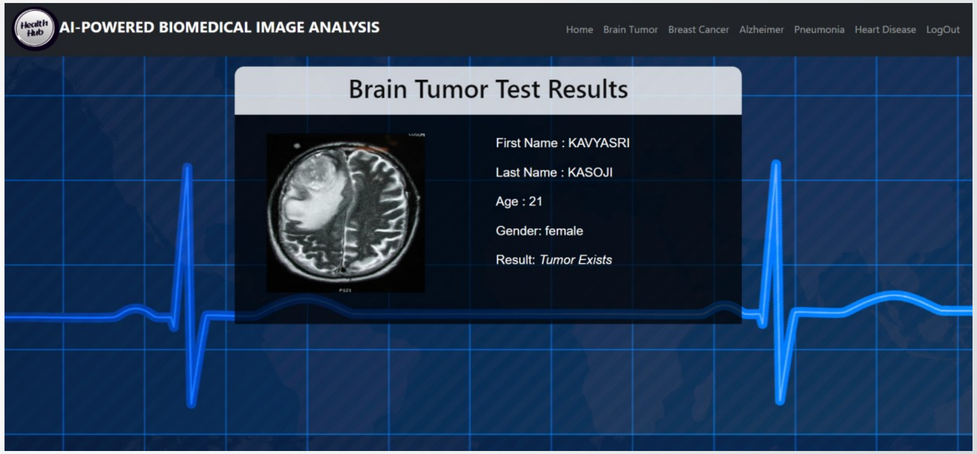


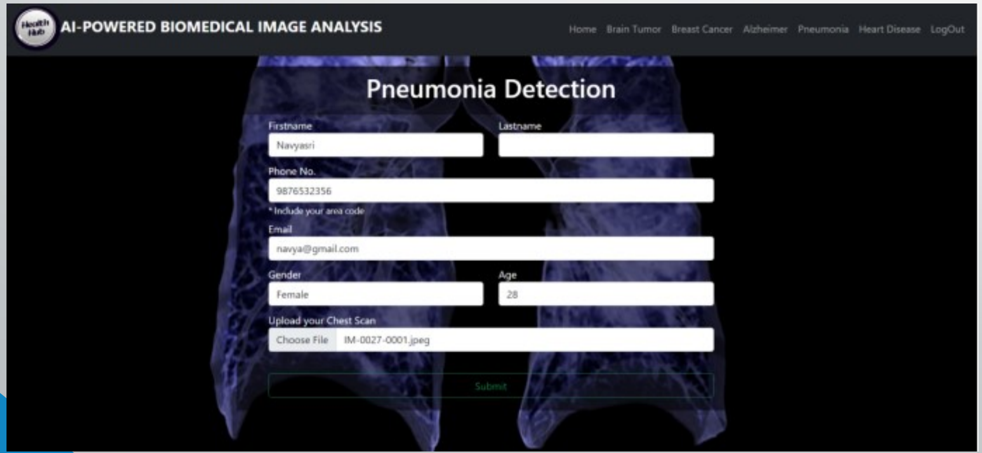


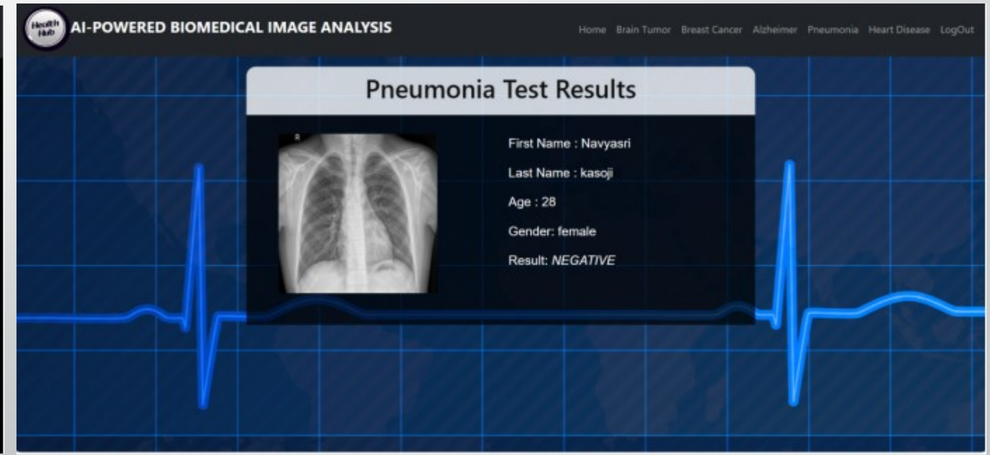


RESULT


AI-POWERED BIOMEDICAL IMAGE ANALYSIS
Home Brain Tumor Breast Cancer Alzheimer Pneumonia Heart Disease LogOut
Brain Tumor Detection
Firstname
KAVYASRI
Lastname
KASOJI
Phone No.
09640884597
* Include your area code
Email
kavyasrikasoji@gmail.com
Gender
Female
Age
21
Upload your Brain MRI
Choose File
Y22.jpg


AI-POWERED BIOMEDICAL IMAGE ANALYSIS
Home Brain Tumor Breast Cancer Alzheimer Pneumonia Heart Disease LogOut
Brain Tumor Test Results
First Name : KAVYASRI
Last Name : KASOJI
Age : 21
Gender: female
Result: Tumor Exists


AI-POWERED BIOMEDICAL IMAGE ANALYSIS
Home Brain Tumor Breast Cancer Alzheimer Pneumonia Heart Disease LogOut
Pneumonia Detection
Firstname
Navyasri
Lastname
Phone No.
9876532356
* Include your area code
Email
navya@gmail.com
Gender
Female
Age
28
Upload your Chest Scan
Choose File
IM-0027-0001.jpeg


AI-POWERED BIOMEDICAL IMAGE ANALYSIS
Home Brain Tumor Breast Cancer Alzheimer Pneumonia Heart Disease LogOut
Pneumonia Test Results
First Name : Navyasri
Last Name : kasoji
Age : 28
Gender: female
Result: NEGATIVE

CONCLUSION

In conclusion, this project presents a robust framework for automated biomedical image analysis, demonstrating the potential of machine learning and web technologies in revolutionizing health care diagnostics. The system's accuracy and user-friendly interface make it a valuable tool for healthcare professionals, contributing to early disease detection and improved patient care. It's like a super-savvy assistant for doctors, helping them look at medical pictures and quickly figuring out if there's anything to be concerned about. The friendly website makes it a breeze for doctors to use, and behind the scenes, our smart system keeps everything tidy and safe..

REFERENCES

[1].A. S. Panayides et al., "AI in Medical Imaging Informatics: Current Challenges and Future Directions," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 7, pp. 1837-1857, July 2020, doi: 10.1109/JBHI.2020.2991043.

[2].R. Buettner, M. Bilo, N. Bay and T. Zubac, "A Systematic Literature Review of Medical Image Analysis Using Deep Learning," 2020 IEEE Symposium on Industrial Electronics & Applications (ISIEA), TBD, Malaysia, 2020, pp. 1-4, doi: 10.1109/ISIEA49364.2020.9188131.

[3].J. Ker, L. Wang, J. Rao and T. Lim, "Deep Learning Applications in Medical Image Analysis," in IEEE Access, vol. 6, pp. 9375-9389, 2018, doi: 10.1109/ACCESS.2017.2788044.

[4].Alvin Rajkomar, Sneha Lingam, and Andrew Taylor, "Machine learning in medical imaging: A review", Medical Imaging and Augmented Reality, 2018, doi: 10.1016/j.media.2017.06.005

Thank You!