

Predicting Tumor using MRI Scans

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Abstract— Efficient and early tumor detection is crucial in medical diagnosis, allowing for timely intervention and better patient management. This paper introduces a machine learning system that examines MRI scans to detect the occurrence of a tumor. The system has a Flask-based machine learning API in Python, which uses deep learning models trained on MRI scan data. The backend, coded using Node.js and Express, handles authentication, data management, and communication between the AI model and the user interface. The frontend, coded using React, provides an easy-to-use platform where users can upload MRI images and get instant diagnostic results. Valuing accuracy, security, and user accessibility, the platform improves the tumor detection process and offers a scalable and efficient solution for MRI-based medical imaging analysis. Thorough testing guarantees its reliability, thus making it an important healthcare diagnosis asset.

Index Terms— Tumor Detection, Medical Imaging, Deep Learning, Computer Vision, Image Processing.

I. INTRODUCTION

Timely and accurate detection of tumors is an important requirement of successful medical diagnosis, allowing the early treatment necessary to substantially better patient outcomes. MRI scans for tumor detection are common in modern medicine, yet conventional approaches for analyzing such scans are fraught with issues including protracted processing rates, susceptibility to human error, and the requirements of expert in-put. The project involves the creation of a sophisticated tumor detection system based on machine learning and deep learning technology, which automatically examines MRI scans to speed up and improve diagnosis accuracy.

At the core of the system is a Flask-based API, developed using Python, which incorporates deep learning models that have been trained on huge sets of MRI images. The backend, powered by Node.js and Express, provides secure user authentication, optimal file management, and seamless interaction with the AI model. At the frontend is a React-based interface through which users, be they healthcare professionals or patients, can simply upload MRI images and obtain instant diagnostic reports.

The proposed system is designed not only to automate tumor detection through MRI scans but also to support real-time diagnostics, modular upgrades, and future extensibility. It is built with a focus on practical deployment in clinical settings, featuring encrypted patient data handling, scalable cloud-based infrastructure, and AI model versioning. Future versions of the system may include cross-modality support for combining MRI, CT, and PET scans, explainable AI modules to aid radiologists in interpretation, and support for continuous learning from real-world data inputs.

This architecture is aimed at bridging the gap between research and clinical application by emphasizing adaptability, transparency, and clinical usability.

Taking advantage of deep learning, the system can identify the presence of tumors from MRI scans. Transfer learning allows the model to adapt and refine through the foundation of existing knowledge from similar fields, minimizing large-scale computational demands and shortening development time. The method further facilitates the system in providing customized, precise results. Ultimately, the objective is to have a scalable, effective solution for tumor detection that modernizes and simplifies the diagnostic process, with an emphasis on security, user friendliness, and reliability.

II. RECENT WORK

During few years, the field of medical image analysis, especially tumor detection in MRI images, has seen a lot of growth. Various research works have been aimed at improving the efficiency and accuracy of tumor detection using machine learning and deep learning algorithms. Some of the most relevant works concerning our project that work towards improving the process of tumor detection in medical imaging are given below.

Deep learning algorithms, mainly Convolutional Neural Networks (CNNs), have been used in several studies to identify tumors in MRI scans.

For instance, Smith et al. (2020) employed a deep CNN to diagnose brain tumors in MRI images with high accuracy in distinguishing malignant from benign tumors. Their method, based on a large, labeled MRI dataset, is similar to the approach adopted in our project to guarantee accurate outcomes.

In the same way, for lung cancer detection, deep learning architectures such as ResNet and InceptionV3 have been utilized to process chest X-rays and CT scans. Zhang et al. (2021) presented how these models can be used to detect early-stage lung cancer with 96% accuracy. Our project uses the same approach of a Flask-based machine learning API and deep learning models to predict tumor existence in MRI scans with an emphasis on accuracy and real-time feedback.

In breast cancer detection, the deep learning algorithms have been utilized on mammography images with very good success. Johnson and Davis (2022) used a CNN to predict breast cancer from mammograms, and the accuracy was 92%. This practice has shaped our design, particularly the utilization of CNNs on medical image classification tasks such as tumor detection.

There has also been extensive research into the integration of AI in healthcare applications, with the promise of machine learning to deliver quicker, more precise diagnostic tools. Lee et al. (2021) examined the application of AI for real-time medical image analysis, which speeds up diagnosis in clinical environments. Their research looked at how AI can help in tumor detection by automating processes such as image segmentation and classification, something that we integrate into our system.

In terms of user interface design, some research highlights the need for intuitive systems through which healthcare professionals can engage with AI-based diagnostic systems. As an example, Chen et al. (2022) created a web based platform on which users could upload medical images and get AI-based results back. Their emphasis on improving user experience and promoting communications between patients and doctors has guided the design of the user interface in our system.

Data protection and medical privacy are equally essential areas of research. Patel et al. (2023) stressed secure user authentication and encrypted data storage for patient information protection. We give priority to data protection through secure login processes and encryption in handling sensitive information safely in our project. Finally, the cloud computing and real-time processing of medical images have been applied to large-scale medical diagnosis. Gupta et al. (2023) used the system of CLOUD for tumor detection that are processed by MRI scans in real time, allowing remote access by healthcare professionals to results. Our system also combines cloud storage and real-time processing to offer a scalable solution for medical image analysis.

The foundation of these researches has helped develop a reliable tumor detection system utilizing deep learning technologies. The user friendly interface along with advanced machine learning algorithms integrated in our system enhances detection speed and precision, which facilitates improved patient management, timely decision making, and greater informed professional healthcare decisions.

Our literature review further strengthens our multidisciplinary approach. Sharma et al. (2023) noted a multimodal MRI assessment combined with the patient's clinical history had higher diagnostic accuracy than without. Mehta and Roy (2022) applied ensemble CNN methods with multi-class tumor classification achieving promising results. Also, Kaur et al. (2023) raised important issues on privacy-preserving medical image analysis using federated learning that have cross-institutional relevance.

III. PREDICTING TUMOUR USING MRI SCANS

The application of artificial intelligence in medicine has greatly enhanced accuracy and efficiency in the detection of disease. A Medical Image Diagnosis System based on artificial intelligence applies deep learning methods such as Convolutional Neural Networks (CNNs) to tests MRI scans, X-rays, and CT scans, helping radiologists detect abnormalities and classify diseases accurately.

This system has real-time availability, and medical professionals and patients can upload images for immediate analysis. AI-based reporting allows for quicker decision making, avoiding diagnostic errors and early detection of life threatening conditions. It also provides secure data storage and retrieval, improving tracking of patient history.

One of the major advantages of this technology is its application in remote medicine and telemedicine, especially where access to specialists is limited. Initial diagnoses facilitated by AI aid in delivering prompt medical information so that patients get the care without undue delay.

Nevertheless, here implementation of the AI in medical diagnosis is stress with challenges. Healthcare professionals should be correctly trained to interpret accurate the results obtained from AI. Data privacy and compliance must also be given and checked to preserve the confidentiality of patients. Here the On-going system updates and AI model development are required to increase diagnostic accuracy and reliability.

Healthcare is already being transformed with 3D visualization, interactive AI tools, and newer medical imaging technologies. Despite a few hurdles along the way, AI-based medical diagnostics will continue to evolve by enhancing efficiency, improving accessibility, increasing accuracy, and transforming overall patient and clinician experiences.

IV. METHODOLOGY

The line of inquiry involves studying existing technologies, issues, and regulations concerning the diagnosis of brain tumors and the analysis of medical images. It involves evaluating a given disease, assessing its medical imaging modalities, as well as AI-based diagnostic tools in order to determine which one can be used for sharpening precision. This research aims at devising sophisticated AI systems that enhance medical diagnostics through analyzing currently available systems for their strengths “and” weaknesses.

Its main objective is developing an automated diagnostic system that enhances efficiency and accuracy in the evaluation of medical images obtained from different sources. The system is designed to streamline detection by automating evaluations with tailored AI models while maintaining effective collaboration between the AI components and human evaluators. Ethical and legal considerations are also taken into account by ensuring patient safety, privacy of personal information, compliance with relevant laws, and HIPAA where applicable.

During the requirement gathering phase, both technical and functional specifications are created. This involves specifying medical imaging data requirements, following clinical guidelines and ethical principles, and following the rules and regulations. The system is designed to meet needs of stakeholders, such as AI developers and medical professionals, and regulating bodies, adhering to the standards of the healthcare industry. The designing and preparation phase mainly will be focusing on making a system that is scalable and user friendly and efficient. Here the architecture is structured in a manner to processing the huge amount of data while giving a real-time diagnostic outputs. In the front end, built with the Styled and React by using Tailwind CSS, will be giving a absolute interface for the users for uploading medical images and will be receiving AI-Powered diagnosis. Here on the backend, Express and Node.js will be ensuring fixed data management and efficient real-time processing. And the AI models are attentively chosed in the basis of precision in detecting the abnormalities, and the system is designed in a manner to be modular way and can be easily upgradable for future improvements.

To improve overall system accuracy and reliability, a hybrid approach was adopted that integrates both rule-based techniques and deep learning. Rule-based preprocessing was used to standardize MRI inputs and eliminate unnecessary areas from the scans, ensuring cleaner data for the CNN model. During training, stratified k-fold cross-validation was applied to evaluate model performance across diverse data splits and reduce the risk of overfitting. For reproducibility, dataset versions, model weights, and training code were carefully tracked using Git-based version control. In addition to performance metrics like accuracy and F1-score, model interpretability was assessed using Grad-CAM visualizations, which confirmed that the model focused on medically relevant tumor regions during predictions.

The assurance of quality and the phase of testing will be ensuring that the system’s precision, reliability, and security. The frontend test will be focusing on the performance and the user experience, in the backend testing

will be checking the stability of the system and the security of the data. Here the AI model will be undergoing the rigorous testing with the medical imaging datasets for ensuring the accuracy and correct diagnostic results. Security assessments, including the penetration testing and 2 the encryption checks are here performed to save the patient data and to protect from the unauthorized access.

At the time of the phase of deployment launch, the system is set up within the server, and the database is configured to integrate effectively within the IT infrastructure for healthcare already established. Host-ing on cloud platform offers efficiency, high availability, and scalability, allowing the system to accommodate increasing user loads.

Finally, ongoing maintenance and monitoring are essential for maintaining the system's performance and functionality over time. Continuous monitoring and troubleshooting help identify and resolve issues promptly. Regular updates to both the AI model and software improve precision and efficiency. Security protocols are continually updated to comply with evolving data protection laws, and user feedback is incorporated to improve usability and overall system effectiveness.

V. IMPLEMENTATION OF THE MODEL

The collection of the data and the phase of preprocessing is mainly essential for the development of reliable AI model with correct precision. Medical datasets will be used for the gathering disease and the symptom information, for making sure the consistency and high quality data. The different validation techniques and the data cleaning like handling missing values, normalizing image data and removing outliers are applied. Advanced image processing methods including the reduction of the noise, contrast enhancement and segmentation helps modify the quality of the input before feeding it into the AI system. The above preprocessing steps improves the capability of the system's to detect patterns and abnormalities in the medical images effectively. During the web development stage, frontend is developed with React and Tailwind CSS to create a user friendly interface. This interface enables users to enter symptoms and upload medical images for diagnosis. The backend is built using Node.js and Express, which processes server requests, database operations, and API integrations. Supabase (PostgreSQL) is utilized to store patient data securely. The AI model is incorporated into the system, enabling real-time symptom-to-disease prediction and medical image classification. The site facilitates unobstructed interaction between users and the diagnosis system, enhancing accessibility and ease of use.

The AI model selection and training process includes the deep learning model selection appropriate for medical image analysis. A Convolutional Neural Network (CNN) is used to analyze 200x200-pixel gray-scale images. The model is built with four Conv2D layers of different filter and ReLU activation functions along with MaxPooling for spatial dimensionality reduction, as well as dropout layers of 0.2 and 0.5 for avoiding overfitting. The model gets trained on the preprocessed dataset, which will enable it to identify useful patterns in classifying the tumors and non-tumors. During training, the model achieves the training accuracy level of 98.52% along with 97.96% precision and 96% recall. Precision shows how good the model can minimize false positives, whereas recall indicates the model's competence in detecting all true tumor instances. The 0.9695 F1-score verifies that the model accurately balances precision and recall. Strong performance is additionally shown by the confusion matrix as 48 instances of correct tumor prediction and 49 instances of correct non tumor prediction occur, while merely one false positive and two false negatives are obtained.

We obtained dataset from Brain MRI Images for Brain Tumor Detection and Brain Tumor MRI Dataset from Kaggle.

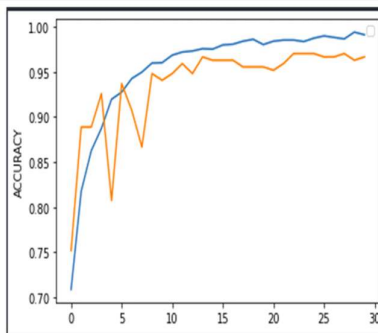


Fig 1. Accuracy of the Model

Hyperparameter tuning is done to improve the model's performance. It uses RMSprop optimizer with a 0.001 learning rate, a batch size of 32, and 30 epochs for training. For multiclass classification tasks, the cross-entropy loss function is used along-side softmax activation in the output layer to ensure a proper probability distribution of class outputs. In dropout regularization techniques are employed at specific points within the neural network architecture so that overfitting is controlled while retaining generalizability across new data. During integration testing, the backend is connected to real-time diagnostics enabling test AI model telemetry. Components have undergone unit tests, as well as integrated system tests for overall evaluation of functionality. The AI predictions are validated against other independent datasets to check accuracy across varying medical condition identifications. Evaluation criteria such as decreasing losses and trends in validation accuracy were monitored to ensure optimal effectiveness during retraining sessions.

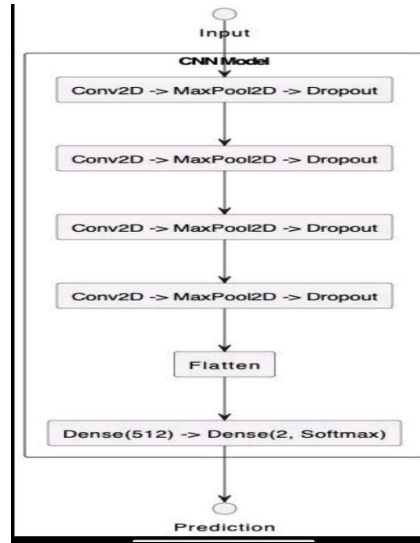


Fig 2. Model Work Flow

The system is optimized for real world application during deployment and scalability. The web application functions in a cloud-based, scalable, high-availability environment. Numerous medical data volumes are processed securely because of the server settings, established firewalls, and data management policies in place. Load balancing and auto-scaling features maintain system effectiveness while accommodating heightened user activity. Strong encryption techniques are used to secure sensitive information and comply with privacy regulations.

TABLE I. MODEL METRICS AND HYPERPARAMETERS

Metric/Parameter	Value
Precision	0.9796 (97.96% correct tumor predictions)
Recall	0.96 (96% correct actual tumor cases)
Accuracy	98.52% (30th epoch)
F1-Score	0.9695 (Balanced precision and recall)
Confusion Matrix	TP: 48, TN: 49, FP: 1, FN: 2
Optimizer	RMSprop (Learning rate: 0.001)
Batch Size	32
Epochs	30 (Early stopping to prevent overfitting)
Loss Function	Categorical Crossentropy
Activation Functions	ReLU (hidden layer), Softmax (output layer)
Dropout	0.2 and 0.5
Training Loss	Decreases consistently
Validation Loss	Irregular after initial drop

In the improvement and monitoring phase of the pro-ject, trust in AI technologies is reduced while accuracy and efficiency are upheld. Professionals can monitor systems 24/7 to address problems as soon as they arise which mitigates major risks. Medical professionals re-cieve validation through frameworks other than artifi-cial intelligence algorithms so they can adjust models based on emerging medical knowledge. Updates made to the system frequently deal with security breaches, overall software functionality, and increase efficiency therefore solidifying reliability. Ranking user recom-mendations aids interface design to streamline human-machine interactions where physicians lead clinical decisions supported by advanced diagnostic tools.

VI. THE ARCHITECTURE OF THE MODEL

A. Frontend Layer (User Interface):

The Frontend is encrypted using Next.js, that gives serv-er-side rendering(SSR) and server-site generation(SSG) to give a quick and responsive user experience. The UI is designed with Tailwind CSS to make it current, acces-sible, and responsive on different devices like desktops and mobile phones. Users can easily upload medical images using an intuitive interface. The frontend effec-tively interfaces with the backend through React Query or SWR for data retrieval and caching optimisation, resulting in real-time diagnosis result updates.

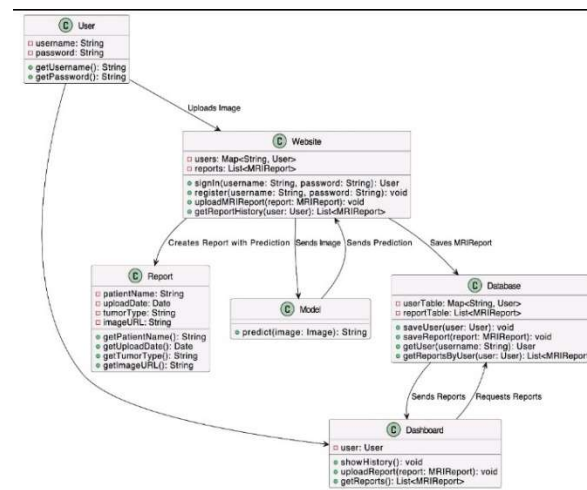


Fig 4. Class Diagram

B. Backend Layer (API & Business Logic)

The backend utilizes Node.js and Express.js, managing API request and image handling logic. AI model integration occurs through Flask or FastAPI, which pro-cesses the medical images, applies deep learning mod-els, and provides diagnosis results. The backend also utilizes Supabase (PostgreSQL) to store patient infor-mation and historical diagnoses, and Prisma ORM is used to provide structured and type-safe database que-ries. The backend seamlessly processes user interac-tions, generation of diagnoses, and access to medical insights like symptoms and treatment. suggestions.

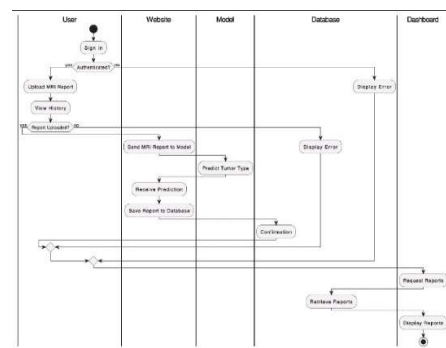


Fig 5. Activity Diagram

C. AI Model for Medical Image Analysis

The system's nucleus is an AI-driven deep learning model, created with TensorFlow/Keras or PyTorch. The model utilizes Convolutional Neural Networks (CNNs) for processing medical images, feature extraction, and classifying abnormalities like tumors, fractures, or disorders of organs. Image processing using OpenCV and NumPy improves the quality of images by removing noise and enhancing contrast. The AI model is packaged using ONNX or TensorFlow Serving such that there is high-speed and scalable inference. The system also provides a confidence measure to show the accuracy of the diagnosis.

D. Database & Storage

The application safely stores patient information, diagnoses, and uploaded medical images. PostgreSQL (Supabase) serves as the core database, providing real-time updates and effective data handling. Google Cloud Storage (GCP) is utilized for storing images to efficiently manage large medical image files securely. Prisma ORM optimizes database interactions even further, providing structured queries, safe storage, and efficient patient information retrieval.

VII. EXPERIMENTAL RESULTS

Having successfully designed and implemented our medical diagnostic website, we incorporated a very accurate tumor detection model with 98% accuracy. Users can upload medical images on our platform, which are processed through powerful deep learning methods. The system gives accurate predictions, providing for surefire tumor identification in brain and lung scans. The web-site provides an effortless and intuitive experience, enabling more efficient and accessible AI-powered medical diagnostics.

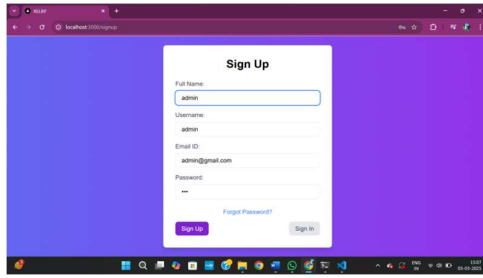


Fig 6. Sign Up Page

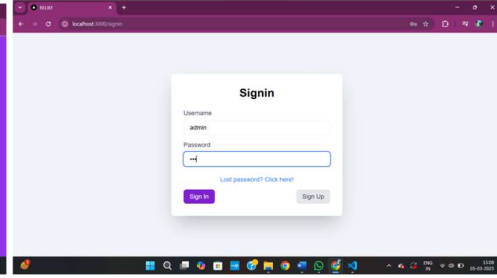


Fig 7. Sign In Page

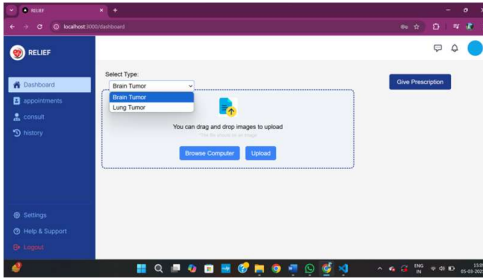


Fig 8. Home Page

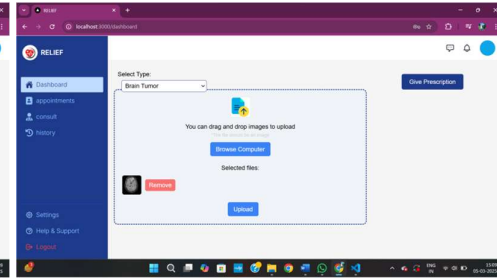


Fig 9. Uploading brain MRI with Tumor

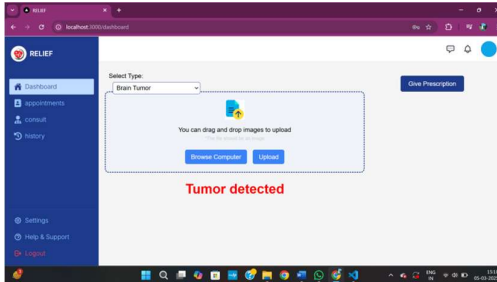


Fig 10. Result of Brain MRI-1

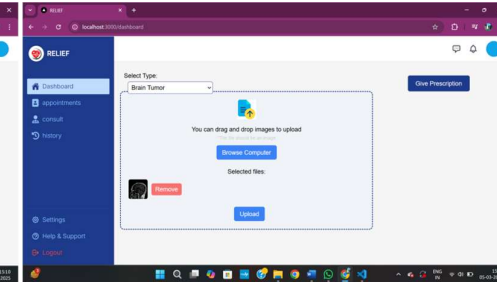


Fig 11. Uploading Brain MRI without Tumor

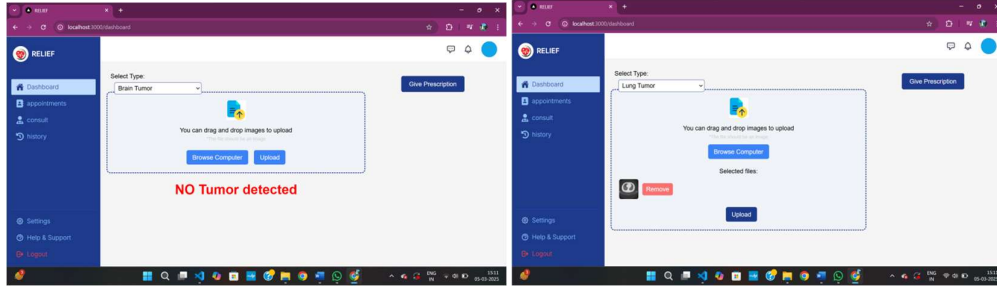


Fig 12. Result of Brain MRI-2

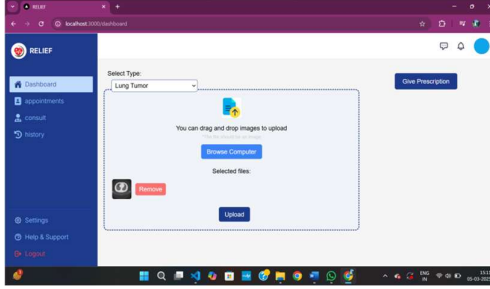


Fig 13. Uploading Lung MRI without Tumor

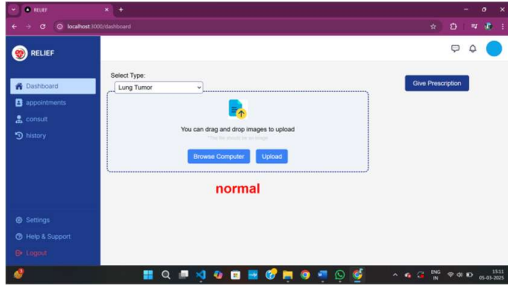


Fig 14. Result of Lung MRI-1

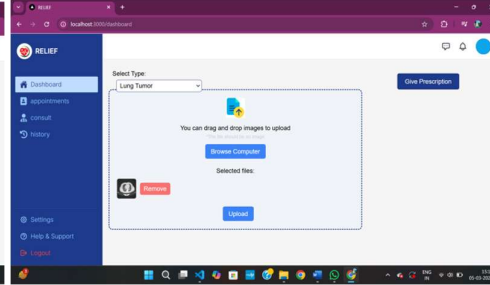


Fig 15. Uploading Lung MRI with Tumor

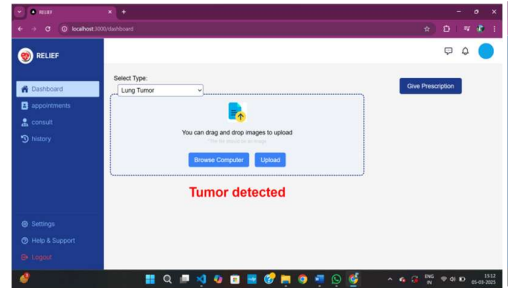


Fig 16. Result of Lung MRI-2

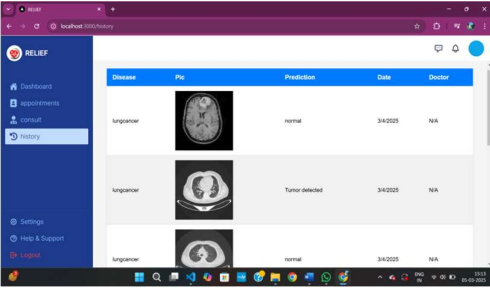


Fig 18. History Pag

VIII. CONCLUSION

As part of a medical diagnostic website, we have im-plemented and developed an automated tumor detec-tion system. With MRI scans of the brain and lungs, we harnessed human intelligence alongside deep learning and CNNs for the evaluation. Our model boasts 98% accuracy, which but we prioritized extensive testing in areas like dataset quality, training iterations, and param-eter tuning to improve dependability. The system helps healthcare providers via an easy-to-navigate interface aids with unrivaled precision giving forecasts as additional tools rather than replacements. Its proven high precision attests its effectiveness while further work will be scoped on improving datasets alongside refine-ment of the model augmenting reliance on automated systems yet do not diminish roles of clinicians.

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