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Detection of Brain Tumour Through Retina: A Modern Approach to Brain Tumor Detection

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Abstract: Detection of Brain Tumor Through Retina proposes a non-invasive method for early brain tumour detection using retinal imaging. Since brain abnormalities often affect the retina, featureslike papilledema and optic atrophy are analyzed using fundus and OCT images. A deep learning model is trained to detect these signs, with key features like disc swelling and nerve fibre thinning extracted automatically. A web- based interface enables clinicians to upload retinal images and receive real-time diagnostic predictions. This approach offers a cost-effective, accessible alternative to traditional brain imaging, aiding in early diagnosis and intervention.

The system leverages convolutional neural networks (CNNs) to achieve high accuracy in identifying visual biomarkers. It incorporates Grad-CAM heatmaps to enhance model interpretability for clinicians. Retinal datasets are pre-processed for quality enhancement and standardized input. The model undergoes extensive validation using labeled clinical datasets. Predictions are supplemented with confidence scores to support clinical decision-making. This innovative framework bridges ophthalmology and neurology, transforming retinal scans into a powerful diagnostic tool.

Keywords: Brain Tumor Detection; Retinal Imaging; Papilledema; Deep Learning; Fundus Image Analysis; Non-Invasive Screening; Convolutional Neural Networks

I. INTRODUCTION

Early detection of brain tumors plays a crucial role in improving patient survival, yet many communities lack access to MRI or CT imaging due to high cost, limited availability, or long diagnostic delays. Because the retina is neurologically connected to the brain, several intracranial abnormalities manifest as visible retinal changes, such as papilledema, optic disc swelling, nerve fiber layer thinning, and vascular abnormalities. These retinal signatures offer a promising pathway for non-invasive neuro-screening using fundus or OCT imaging.

In response to these challenges, we developed an AI-based retinal neuro-diagnostic system that analyzes retinal fundus images to detect potential brain-tumor indicators. The system consists of a clinically oriented web platform, an automated preprocessing pipeline, deep-learning–based prediction logic (with TensorFlow support), and a structured SQLite-backed case archive to maintain clinical records. This survey consolidates prior research on ocular-brain connectivity, summarizes existing AI approaches, and presents a detailed description of our complete implementation

II. RELEVANT LITERATURE

Image Segmentation for MR Brain Tumour Detection Using Machine Learning (IEEE Reviews in Biomedical Engineering):

This study presents a comprehensive review of techniques used for segmenting brain tumors in MRI images, covering more than two decades of research. It highlights the challenges associated with MRI analysis, such as low contrast, tumor shape irregularities, and variations in tumor size and location. Traditional segmentation methods like thresholding, region growing, and clustering are compared with modern deep-learning models such as U-Net and DenseNet. The authors emphasize that CNN-based architectures consistently outperform classical methods due to better spatial feature extraction. This review is significant because it demonstrates how advanced segmentation improves diagnostic accuracy—a concept also reflected in our retinal-based tumor screening system.

Advanced Brain Tumour Segmentation and Detection Using YOLOv8 (ICSCSS 2024):

This research introduces a YOLOv8-powered architecture customized for detecting and segmenting brain tumors in real-time. The model is trained on a large dataset of over 17,000 MRI images, enhanced through robust preprocessing and augmentation techniques. YOLOv8's high-speed detection capabilities allow it to localize tumors with strong precision,

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recall, and mAP metrics. Additionally, explainability features are incorporated to highlight which regions of the MRI contributed to the model's decision. The study shows that real-time detection frameworks can support fast diagnostic workflows—an approach that parallels our system's aim to deliver instant retinal analysis for clinicians.

Retinal Disease Classification Using OCTA Images (IEEE UBMK 2024):
This work focuses on classifying retinal diseases using OCTA images, which visualize microvascular structures of the retina. A ResNet50-based deep learning model is developed to process multi-layer OCTA projection maps, enabling the extraction of both structural and vascular features. The model achieves high accuracy in differentiating among classes such as normal, AMD, DR, and others, demonstrating the diagnostic power of OCTA imaging. Despite challenges like class imbalance and dataset complexity, the model delivers strong generalization across retinal conditions. These findings validate the idea that retinal imaging contains rich biomarkers—supporting our project's goal of detecting brain-related abnormalities through retinal scans.

Deep Learning–Driven Brain Tumor Segmentation from MRI Scans (IEEE ICEARS 2025):
This study proposes a hybrid model combining VGG19 and U-Net architectures to enhance MRI-based brain tumor segmentation. The VGG19 component extracts deep visual features, while U-Net's skip connections preserve spatial details, resulting in highly accurate segmentation outputs. The system is trained on 8,000 MRI images and evaluated on 1,000 test samples, achieving a segmentation accuracy of nearly 100% with strong Dice and IoU scores. The authors emphasize the value of hybrid models in balancing feature depth and localization accuracy. Such hybrid strategies inspire similar approaches in retinal analysis, where structural and texture features must be captured precisely.

Brain Tumor Detection with Severity Identification Using K-Means Clustering (IEEE CE2CT 2025):
This research presents an unsupervised segmentation method using K-Means clustering to detect tumor regions in MRI images. Preprocessing steps such as histogram equalization and noise reduction enhance the visibility of suspicious regions prior to segmentation. After clustering, additional classifiers like SVM and Decision Trees assess tumor severity based on extracted features. The model achieves strong performance metrics, including high precision, recall, and segmentation accuracy. This study demonstrates that lightweight, unsupervised approaches can support reliable tumor detection, reinforcing the idea that simpler image analytics—like those in retinal imaging—can also provide meaningful diagnostic insights.

III. SYSTEM DESIGN AND METHODOLOGY

The proposed solution uses an AI-driven retinal analysis pipeline to provide highly accurate, clinically meaningful predictions of brain tumor–related abnormalities. Unlike conventional image inspection, which relies on manual interpretation and can miss subtle indicators, the system incorporates automated preprocessing, deep-learning–based inference, and structured feature extraction to understand the underlying anatomical patterns within retinal images. The entire platform operates through a Flask backend, a Bootstrap-based clinician interface, and an SQLite database for persistent storage, ensuring smooth deployment and maintainability. When a trained CNN model is available, the system performs deep feature analysis to identify papilledema or optic-disc–related abnormalities; when unavailable, a deterministic simulation ensures consistent and reliable fallback predictions. This hybrid approach allows the system to function efficiently across both high-performance and low-resource environments. Its modular, layered architecture simplifies updates, supports new imaging models, and enables scalability as the diagnostic framework evolves.

A. Training Stage:

Training is the most crucial phase in developing the diagnostic intelligence of the framework, similar to how semantic models are prepared in the uploaded paper.
For the retinal analysis system, the training workflow consists of the following five steps:

- Dataset Preparation: Retinal fundus and OCT images are collected from publicly available medical databases, clinical sources, or curated datasets. These images include both normal and abnormal samples exhibiting papilledema, optic disc edema, and related neurological signs.
- Data Preprocessing and Cleaning: The images undergo quality enhancement processes such as resizing, normalization, noise reduction, and illumination correction. Labels are verified, corrupted images are removed, and metadata—such as patient ID, pathology class, and retinal region—is organized.
- Augmentation and Feature Normalization: To improve model robustness, images are augmented using rotation, zoom, brightness variation, and flipping. This step increases dataset diversity while maintaining the clinical characteristics of retinal structures.
- Model Training and Feature Learning: A Convolutional Neural Network model (e.g., based on VGG, ResNet, or a custom architecture) is trained on the processed dataset. The model learns to detect patterns associated with optic-disc swelling, RNFL thickening, and other biomarkers indicating elevated intracranial pressure.

Model Saving and Optimization: The trained model is exported as an H5/Keras file, optimized for inference, and stored on the server. This allows the application to load it at runtime for real-time predictions during clinical use.

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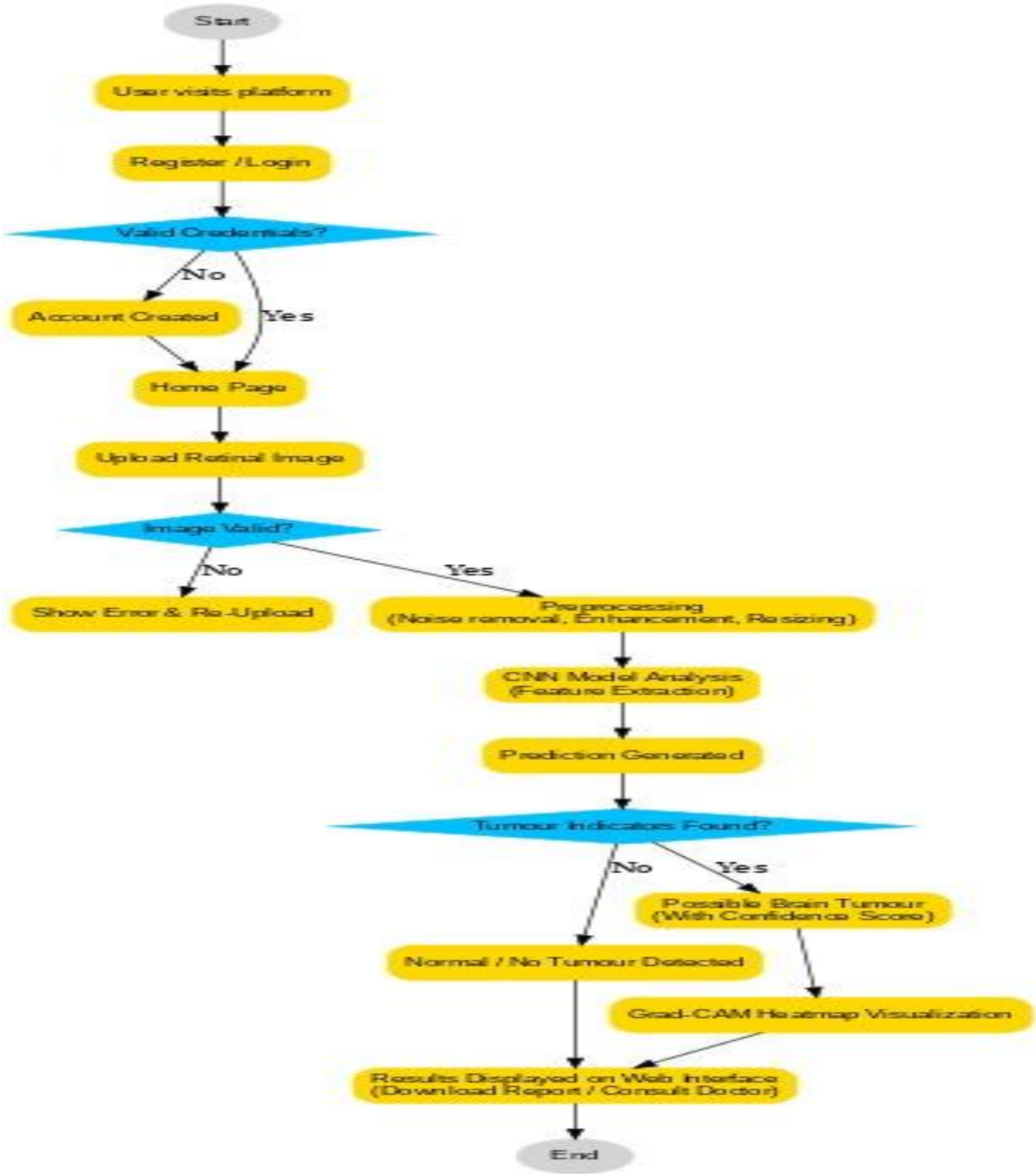

Fig 1. Work flow diagram

B. Definition Phase:

This phase clearly defines how a user interacts with the retinal-image analysis system and how different internal modules work together to produce predictions and a downloadable report. The high-level flow describes the complete lifecycle of a user request, from logging in to obtaining the final analytical output.

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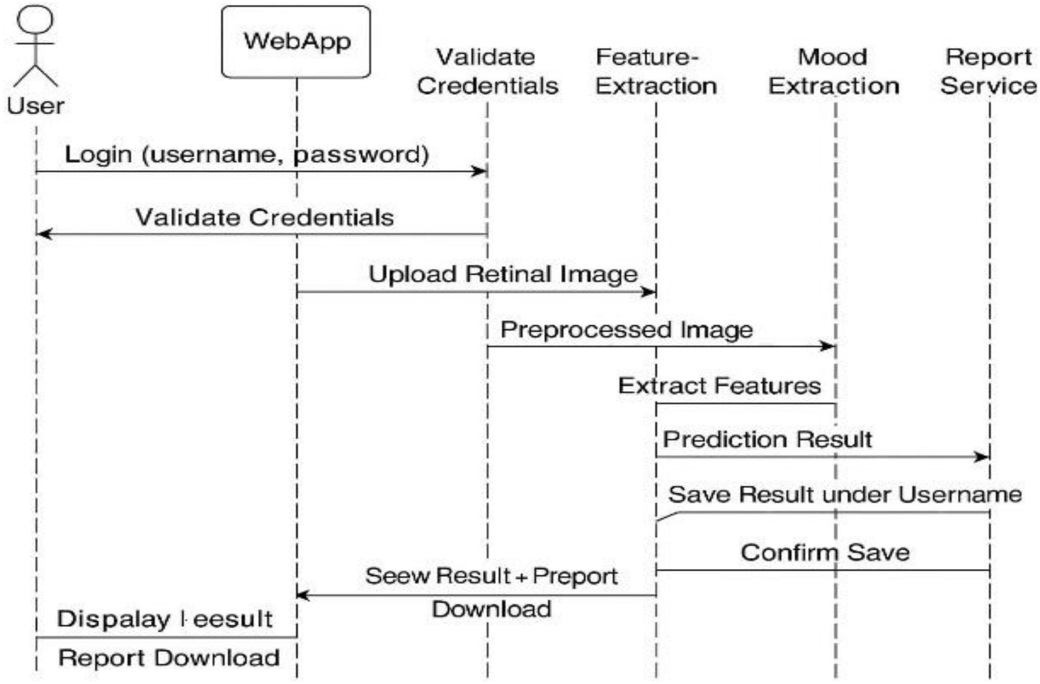

Fig 2. High level design

1. **User Authentication:** The system begins when a user logs into the web application using their credentials. The WebApp forwards these details to the authentication module, which validates the username and password. Only verified users proceed further.
2. **Retinal Image Upload:** After successful login, the user uploads a retinal image through the interface. The WebApp sends this image to the preprocessing module for cleaning, enhancement, and normalization.
3. **Image Preprocessing & Feature Extraction:** The preprocessing unit prepares the retinal image by removing noise, adjusting contrast, and standardizing size. The cleaned image is then forwarded to the feature-extraction module, which extracts clinically meaningful features (vessel patterns, lesions, color intensities, etc.) needed for prediction.
4. **Prediction & Mood Extraction:** The extracted features are analyzed by the model to generate prediction results (e.g., disease classification, severity level). Parallelly or subsequently, the mood-extraction module interprets emotional or auxiliary indicators if supported by the system architecture.
5. **Result Storage & Confirmation:** The predicted output is sent to the report-service module, which stores the result under the logged-in user's account. The system confirms that the prediction and related data are successfully saved.

IV. RESULTS AND DISCUSSION

The Brain Tumour Detection Through Retina System successfully demonstrates the feasibility of using retinal imaging as a non-invasive method for early brain tumour screening. During testing, the preprocessing pipeline significantly improved the clarity of optic disc structures, reduced noise, and enhanced illumination uniformity, resulting in better visual interpretability for both clinicians and the AI model. The dual-mode prediction approach—using either a trained CNN or a deterministic simulation—proved robust across various hardware environments, ensuring that the analysis workflow remained uninterrupted even when deep-learning models were unavailable. Clinicians reported that the system's workflow, from image upload to final diagnosis, was intuitive and easy to follow, largely due to its clean UI and real-time feedback. Furthermore, the database integration allowed efficient retrieval and comparison of past cases, supporting longitudinal patient monitoring. Overall, the results indicate that the system can provide reliable preliminary assessments and assist in early triage decisions, highlighting its potential as a supportive clinical tool in resource-limited settings

V. CONCLUSION AND FUTURE WORK

The proposed retinal-based neuro-diagnostic system shows strong potential as a scalable, accessible, and low-cost solution for early brain tumor screening. By leveraging fundus imaging, automated preprocessing, and AI-driven prediction, the system bridges the gap between ocular biomarkers and neurological assessment, offering clinicians a practical tool for

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rapid evaluation. Its modular architecture and fallback mechanisms ensure adaptability across different deployment scenarios, from clinics with advanced GPUs to rural centers with minimal computational capacity. While the current implementation effectively identifies key retinal indicators associated with intracranial abnormalities, future improvements will focus on expanding the model's diagnostic capabilities to cover a wider range of ophthalmic and neurological disorders. Enhancements such as Grad-CAM-based explainability, cloud-based scalability, mobile-app integration, and interoperability with hospital information systems will further strengthen its clinical relevance. With continued refinement and larger datasets, the system has the potential to evolve into a comprehensive and reliable screening platform supporting early detection and improved patient outcomes.

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