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AI-ENHANCED HEALTH MANAGEMENT APPLICATION FOR PATIENT CARE

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ABSTRACT

Advances in medical imaging and artificial intelligence are transforming how clinicians diagnose and manage neurological conditions. This project develops and evaluates an AI-enhanced health management application that automates brain-tumor classification from MRI scans and consolidates patient–doctor workflows into a single Django-based portal. Two machine-learning pipelines were implemented: a classical approach combining Principal Component Analysis (PCA) for dimensionality reduction with a Support Vector Machine (SVM) classifier, and a deep-learning Convolutional Neural Network (CNN). Both pipelines were trained and tested on the same dataset of four tumor classes (glioma, meningioma, pituitary, and no-tumor). The PCA+SVM model achieved 76.13 % accuracy, 75.21 % precision, 73.86 % recall, and a 73.88 % F1-score. In contrast, the CNN delivered 99.30 % accuracy, 99.22 % precision, 99.41 % recall, and a 99.31 % F1-score, highlighting its superior ability to extract complex spatial features from MRI data.On the web front end, patients and doctors each access role-specific dashboards: patients can register/login, upload MRIs, view annotated results, book appointments, and review prescriptions; doctors can log in, view today's appointments, generate prescriptions, and optionally re-analyze scans. All user and imaging data persisted in a MySQL database, and annotated images are rendered inline via Base64 encoding. The platform thus demonstrates how AI-driven diagnostics and digital workflow automation can converge to improve diagnostic speed, reduce administrative overhead, and enhance patient care.

Keywords:MRI data, Health management, Artificial Intelligence, Brain tumor classification, PCA approach, Support vector machine, Deep learning,Convolutional neural networks

1. INTRODUCTION

Healthcare systems are complex and challenging for all stakeholders, but artificial intelligence (AI) has transformed various fields, including healthcare, with the potential to improve patient care and quality of life. Rapid AI advancements can revolutionize healthcare by integrating it into clinical practice. Reporting AI's role in clinical practice is crucial for successful implementation by equipping healthcare providers with essential knowledge and tools.AI is a rapidly evolving field of computer science that aims to create machines that can perform tasks that typically require human intelligence. AI includes various techniques such as machine learning (ML), deep learning (DL), and natural language processing (NLP). Large Language Models (LLMs) are a type of AI algorithm that uses deep learning techniques and massively large data sets to understand, summarize, generate, and predict new text-based content [1, 2]. LLMs have been architected to generate text-based content and possess broad applicability for various NLP tasks, including text generation, translation, content summary, rewriting, classification, categorization, and sentiment analysis. NLP is a subfield of AI that focuses on the interaction between computers and humans through natural language, including understanding, interpreting, and generating human language. NLP involves various techniques such as text mining, sentiment analysis, speech recognition, and machine translation. Over the years, AI has undergone significant transformations, from the early days of rule-based systems to the current era of ML and deep learning algorithms [3].

Today, AI is transforming healthcare, finance, and transportation, among other fields, and its impact is only set to grow. In academia, AI has been used to develop intelligent tutoring systems, which are computer programs that can adapt to the needs of individual students. These systems have improved student learning outcomes in various subjects, including math and science. In research, AI has been used to analyze large datasets and identify patterns that would be difficult for humans to detect; this has led to breakthroughs in fields such as genomics and drug discovery. AI has been used in healthcare settings to develop diagnostic tools and personalized treatment plans. As AI continues to evolve, it is crucial to ensure that it is developed responsibly and for the benefit of all [5, 6, 7, 8].The rapid progression of AI technology presents an opportunity for its application in clinical practice, potentially revolutionizing healthcare services. It is imperative to document and disseminate information regarding AI's role in clinical practice, to equip healthcare providers with the knowledge and tools necessary for effective implementation in patient care. This review article aims to explore the current state of AI in healthcare, its potential benefits, limitations, and challenges, and to provide insights into its future development. By doing so, this review aims to contribute to a better understanding of AI's role in healthcare and facilitate its integration into clinical practice.

Advances in deep learning, particularly convolutional neural networks, have demonstrated human-level performance in image classification tasks. By harnessing these methods for medical imaging, we can reduce diagnostic latency and human error. At the same time, digitizing administrative processes (registration, appointment booking, prescription generation) can improve patient experience and operational throughput. This convergence of AI and web technologies motivates a unified platform that addresses both clinical and logistical challenges. The main contributions of this work are as follows:

1. Develop and integrate a CNN model capable of accurately distinguishing between glioma, meningioma, pituitary tumors, and normal scans.
2. Implement a PCA-based dimensionality reduction followed by an SVM classifier to compare performance and robustness with the CNN.
3. Build a Django-based interface allowing patients to upload scans, view AI-annotated results, and book appointments; and doctors to review cases and generate prescriptions.
4. Create a dashboard that displays real-time metrics (accuracy, precision, recall, F1) for both AI pipelines to support continuous evaluation.
5. Ensure patient registration, scan analysis, appointment scheduling, and prescription issuance occur in a single, consistent platform with persistent record-keeping.

2. LITERATURE SURVEY

With all the advances in medicine, effective disease diagnosis is still considered a challenge on a global scale. The development of early diagnostic tools is an ongoing challenge due to the complexity of the various disease mechanisms and the underlying symptoms. AI can revolutionize different aspects of health care, including diagnosis. ML is an area of AI that uses data as an input resource in which the accuracy is highly dependent on the quantity as well as the quality of the input data that can combat some of the challenges and complexity of diagnosis [9]. ML, in short, can assist in decision-making, manage workflow, and automate tasks in a timely and cost-effective manner. Also, deep learning added layers utilizing Convolutional Neural Networks (CNN) and data mining techniques that help identify data patterns. These are highly applicable in identifying key disease detection patterns among big datasets. These tools are highly applicable in healthcare systems for diagnosing, predicting, or classifying diseases [10].

AI is still in its early stages of being fully utilized for medical diagnosis. However, more data are emerging for the application of AI in diagnosing different diseases, such as cancer. A study was published in the UK where authors input a large dataset of mammograms into an AI system for breast cancer diagnosis. This study showed that utilizing an AI system to interpret mammograms had an absolute reduction in false positives and false negatives by 5.7% and 9.4%, respectively [11]. Another study was conducted in South Korea, where authors compared AI diagnoses of breast cancer versus radiologists. The AI-utilized diagnosis was more sensitive to diagnose breast cancer with mass compared to radiologists, 90% vs. 78%, respectively. Also, AI was better at detecting early breast cancer (91%) than radiologists 74% [12].

Furthermore, a study utilized deep learning to detect skin cancer which showed that an AI using CNN accurately diagnosed melanoma cases compared to dermatologists and recommended treatment options [13, 14]. Researchers utilized AI technology in many other disease states, such as detecting diabetic retinopathy [15] and EKG abnormality and predicting risk factors for cardiovascular diseases [16, 17]. Furthermore, deep learning algorithms are used to detect pneumonia from chest radiography with sensitivity and specificity of 96% and 64% compared to radiologists 50% and 73%, respectively [18]. Also, a study was done on a dataset of 625 cases to diagnose acute appendicitis early to predict the need for appendix surgery using various ML techniques; the results showed that the random forest algorithm achieved the highest performance, accurately predicting appendicitis in 83.75% of cases, with a precision of 84.11%, sensitivity of 81.08%, and specificity of 81.01%. The improved method aids healthcare specialists in making informed decisions for appendicitis diagnoses and treatment. Furthermore, the authors suggest that similar techniques can be utilized to analyze images of patients with appendicitis or even to detect infections such as COVID-19 using blood specimens or images [19].

AI tools can improve accuracy, reduce costs, and save time compared to traditional diagnostic methods. Additionally, AI can reduce the risk of human errors and provide more accurate results in less time. In the future, AI technology could be used to support medical decisions by providing clinicians with real-time assistance and insights. Researchers continue exploring ways to use AI in medical diagnosis and treatment, such as analyzing medical images, X-rays, CT scans, and MRIs. By leveraging ML techniques, AI can also help identify abnormalities, detect fractures, tumors, or other conditions, and provide quantitative measurements for faster and more accurate medical diagnosis.

Clinical laboratory testing provides critical information for diagnosing, treating, and monitoring diseases. It is an essential part of modern healthcare which continuously incorporates new technology to support clinical decision-making and patient safety [20]. AI has the potential to transform clinical laboratory testing by improving the accuracy, speed, and efficiency of laboratory processes. The role of AI in clinical microbiology is currently progressing and expanding. Several ML systems were developed to detect, identify, and quantify microorganisms, diagnose and classify diseases, and predict clinical outcomes. These ML systems used data from various sources to build the AI diagnosis such as genomic data of microorganisms, gene sequencing, metagenomic sequencing results of the original specimen, and microscopic imaging [21]. Moreover, gram stain classification to gram positives/negatives and cocci/rods is another essential application of using deep convolutional neural networks that reveal high sensitivity and specificity [22]. A published systematic review showed that numerous MLs were evaluated for microorganism identification and antibiotic susceptibility testing; however, several limitations are associated with the current models that must be addressed before incorporating them into clinical practice [23]. For malaria, Taesik et al. found that using ML algorithms combined with digital in-line holographic microscopy (DIHM) effectively detected malaria-infected red blood cells without staining. This AI technology is rapid, sensitive, and cost-effective in diagnosing malaria [24].

The projected benefits of using AI in clinical laboratories include but are not limited to, increased efficacy and precision. Automated techniques in blood cultures, susceptibility testing, and molecular platforms have become standard in numerous laboratories globally, contributing significantly to laboratory efficiency [25]. Automation and AI have substantially improved laboratory efficiency in areas like blood cultures, susceptibility testing, and molecular platforms. This allows for a result within the first 24 to 48 h, facilitating the selection of suitable antibiotic treatment for patients with positive blood cultures [26]. Consequently, incorporating AI in clinical microbiology laboratories can assist in choosing appropriate antibiotic treatment regimens, a critical factor in achieving high cure rates for various infectious diseases.

ML research in medicine has rapidly expanded, which could greatly help the healthcare providers in the emergency department (ED) as they face challenging difficulties from the rising burden of diseases, greater demand for time and health services, higher societal expectations, and increasing health expenditures [27]. Emergency department providers understand that integrating AI into their work processes is necessary for solving these problems by enhancing efficiency, and accuracy, and improving patient outcomes [28, 29]. Additionally, there may be a chance for algorithm support and automated decision-making to optimize ED flow measurements and resource allocation [30]. AI algorithms can analyze patient data to assist with triaging patients based on urgency; this helps prioritize high-risk cases, reducing waiting times and improving patient flow [31]. Introducing a reliable symptom assessment tool can rule out other causes of illness to reduce the number of unnecessary visits to the ED. A series of AI-enabled machines can directly question the patient, and a sufficient explanation is provided at the end to ensure appropriate assessment and plan.

Moreover, AI-powered decision support systems can provide real-time suggestions to healthcare providers, aiding diagnosis, and treatment decisions. Patients are evaluated in the ED with little information, and physicians frequently must weigh probabilities when risk stratifying and making decisions. Faster clinical data interpretation is crucial in ED to classify the seriousness of the situation and the need for immediate intervention. The risk of misdiagnosing patients is one of the most critical problems affecting medical practitioners and healthcare systems. Diagnostic mistakes in the healthcare sector can be expensive and fatal. A study found that diagnostic errors, particularly in patients who visit the ED, directly contribute to a greater mortality rate and a more extended hospital stay [32]. Fortunately, AI can assist in the early detection of patients with life-threatening diseases and promptly alert clinicians so the patients can receive immediate attention. Lastly, AI can help optimize health care sources in the ED by predicting patient demand, optimizing therapy selection (medication, dose, route of administration, and urgency of intervention), and suggesting emergency department length of stay. By analyzing patient-specific data, AI systems can offer insights into optimal therapy selection, improving efficiency and reducing overcrowding.

3. PROPOSED METHODOLOGY

The proposed system combines advanced image-classification with a straightforward doctor–patient scheduling and record-keeping portal, demonstrating how AI can be embedded into a full-stack web application to automate diagnostic tasks and streamline clinical workflows.

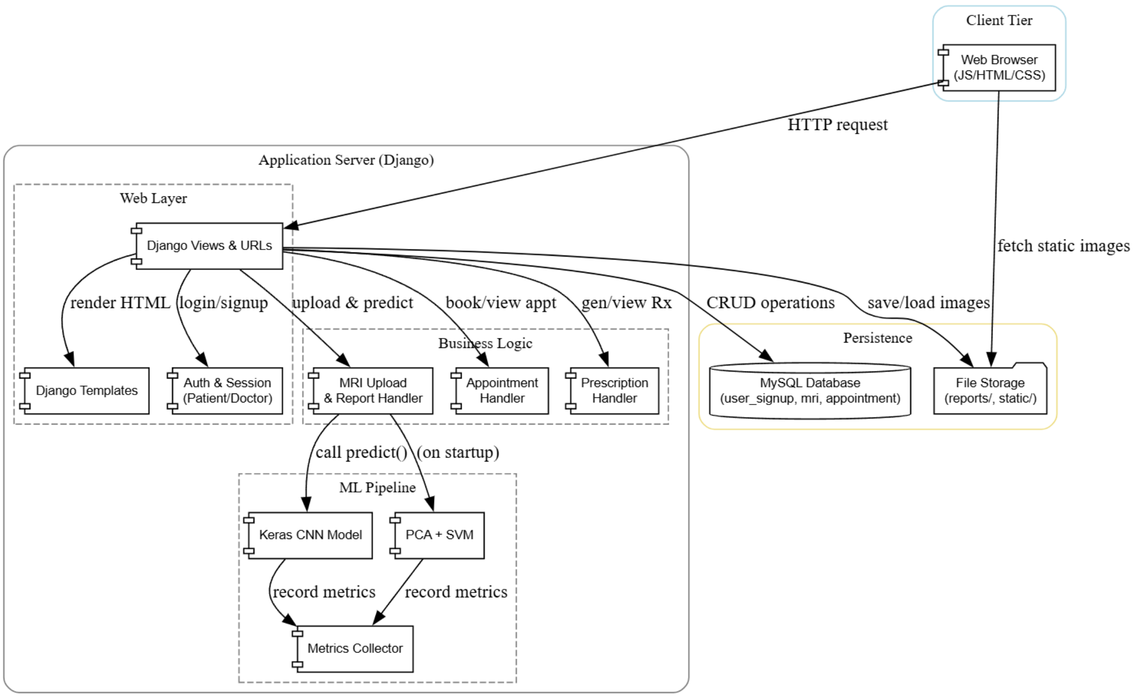

Fig. 1: Proposed system architecture of AI-enhanced healthcare management.

This Django-based web application combines automated brain-tumor classification with a patient–doctor management portal: at startup it loads and normalizes MRI data, trains both a PCA+SVM pipeline and a pretrained Keras CNN—displaying their accuracy, precision, recall, and F1 scores on the dashboard—then waits for real-time use. Patients log in to upload MRI scans via an HTML form, triggering a helper function that resizes the image for the CNN, predicts one of four tumor classes, overlays the result on the image, encodes it for display, and records the filename, patient, label, and timestamp in a MySQL “mri” table. Meanwhile, a MySQL-backed user system lets patients and doctors sign up and log in; patients browse and book appointments with doctors using dynamic date pickers, while doctors view today’s pending appointments and generate prescriptions. All appointments, prescriptions, and uploads are persisted via PyMySQL in the doctorpatientapp database. Thus, the system delivers an end-to-end workflow—from model training through interactive MRI analysis to appointment scheduling and clinical record keeping—within a unified Django framework.

3.1 Proposed CNN Architecture

The stacked sequence of convolution, activation, and pooling progressively distils raw pixel data into high-level representations, which the dense layers then use to make the final classification. The layer-by-layer explanation is as follows:

1. Input (32×32×3): The model accepts a 32×32 color image (three channels).
2. Conv2D → ReLU (32 filters, 3×3 kernel)
    - Learns 32 spatial feature detectors, each looking for patterns in a 3×3 neighborhood.
    - ReLU adds non-linearity, zeroing out negative activations.
3. MaxPooling2D (2×2): Downsamples feature maps by a factor of 2, reducing spatial dimensions and enforcing translation robustness.
4. Conv2D → ReLU (64 filters, 3×3): Learns a richer set of 64 features, again with ReLU activation.
5. MaxPooling2D (2×2): Further reduces map size, focusing on the most salient features.
6. Conv2D → ReLU (128 filters, 3×3): Captures increasingly complex patterns at a deeper layer.
7. MaxPooling2D (2×2): Third downsampling stage, yielding a very compact spatial representation.
8. Flatten: Converts the final pooled feature maps (e.g. 4×4×128 = 2048 values) into a single 1D vector for dense layers.
9. Dense (128 units) → ReLU: Fully connected layer integrating all features; ReLU again introduces non-linearity.
10. Output Dense (4 units) → Softmax: Produces a probability distribution over the four tumor classes (glioma, meningioma, notumor, pituitary), with the highest probability indicating the predicted class.

4. RESULTS AND DISCUSSION

Glioma Tumor (glioma_tumor): Gliomas are tumors that originate from glial cells in the brain or spine. They are the most common type of brain tumor and can be either benign or malignant.Gliomas often appear as irregularly shaped masses with heterogeneous signal intensities on MRI.

Meningioma Tumor (meningioma_tumor): Meningiomas are tumors that arise from the meninges, the layers of tissue covering the brain and spinal cord. They are usually benign but can cause symptoms due to their size or location.Meningiomas typically appear as well-circumscribed, uniformly enhancing masses on MRI, often attached to the dura.

No Tumor (no_tumor): This label indicates that the MRI scan does not show any signs of a brain tumor. The brain appears normal, without any abnormal masses or growths.The MRI scan would display normal brain anatomy with no signs of mass effect, abnormal growths, or other pathologies.

Pituitary Tumor (pituitary_tumor): Pituitary tumors are growths that occur in the pituitary gland, a small gland located at the base of the brain. These tumors can affect hormone levels and may cause various symptoms.Pituitary tumors often appear as small masses within the sella turcica, sometimes with extension into surrounding structures. They are typically well-circumscribed and may enhance with contrast.

9.3 Results Analysis

Figure 2 demonstrate all visitors with three primary actions: "Patient Login," "Doctor Login," and "New User Signup." Clearly labeled buttons or links guide users to the appropriate authentication or registration form, setting the stage for role-based access.

Appointment Booking → Prescription Viewing

In Fig. 3**,** a table displays each doctor's name, phone, email, address, and specialty description. A "Click Here to Book Appointment" link next to each entry invites the patient to choose a date.Fig. 4 lists all of the patient's appointments in tabular form, including appointment ID, doctor name, disease details, prescription text, appointment date, and booking date. Patients can easily track which visits generated which treatments.Fig. 5 shows a table of all patients booked for the current date, with fields for appointment ID, patient name, disease details, and a "Click Here for Prescription" link where prescription text is still "Pending."

Fig. 2: Home page of proposed AI-enhanced health management application for patient care (patient login, doctor login, and new user signup (i.e., doctor or patient)).

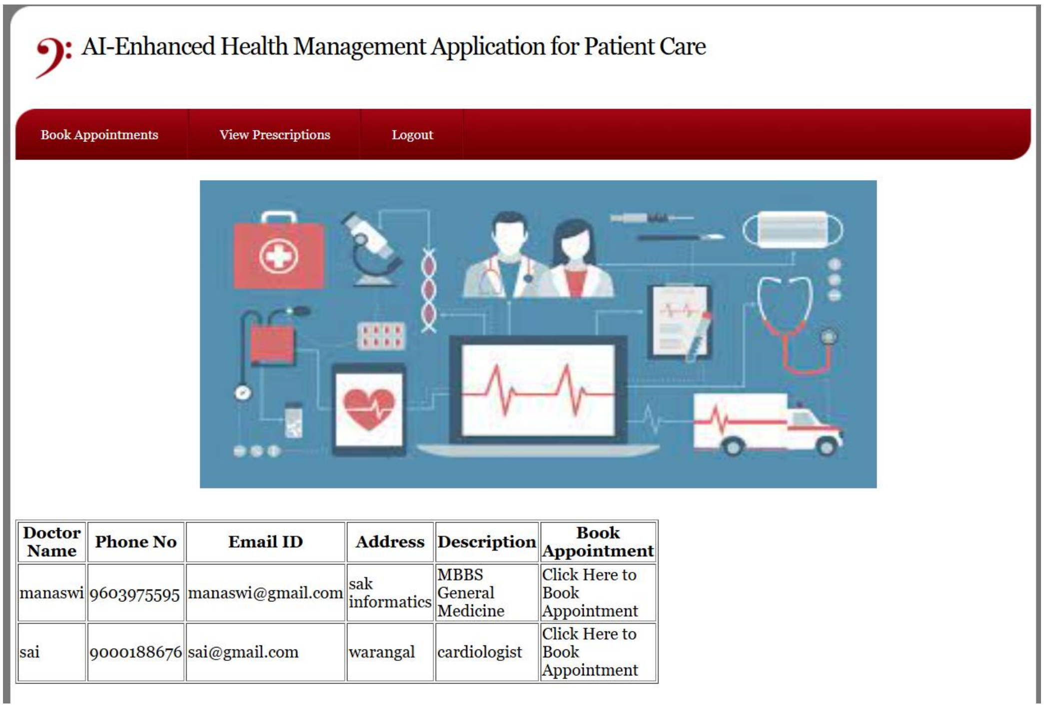

Fig. 3: Book appointments page showing the doctor names with details.

MRI Upload & AI Prediction

In Fig. 6, two example outputs showing the uploaded MRI with the overlaid AI label:

- **(a)** No tumor: The model correctly classifies a healthy scan.
- (b) Meningioma tumor: The model flags the presence of a meningioma.

From Table 1, the CNN massively outperforms the PCA+SVM pipeline across all metrics, achieving around 99 % in accuracy, precision, recall, and F1-score. The SVM approach, while respectable, tops out around 76 % accuracy and 74 %–75 % on the other measures, reflecting that the deep-learning model captures far richer spatial features from the MRI data.

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Fig. 4: View prescriptions page.

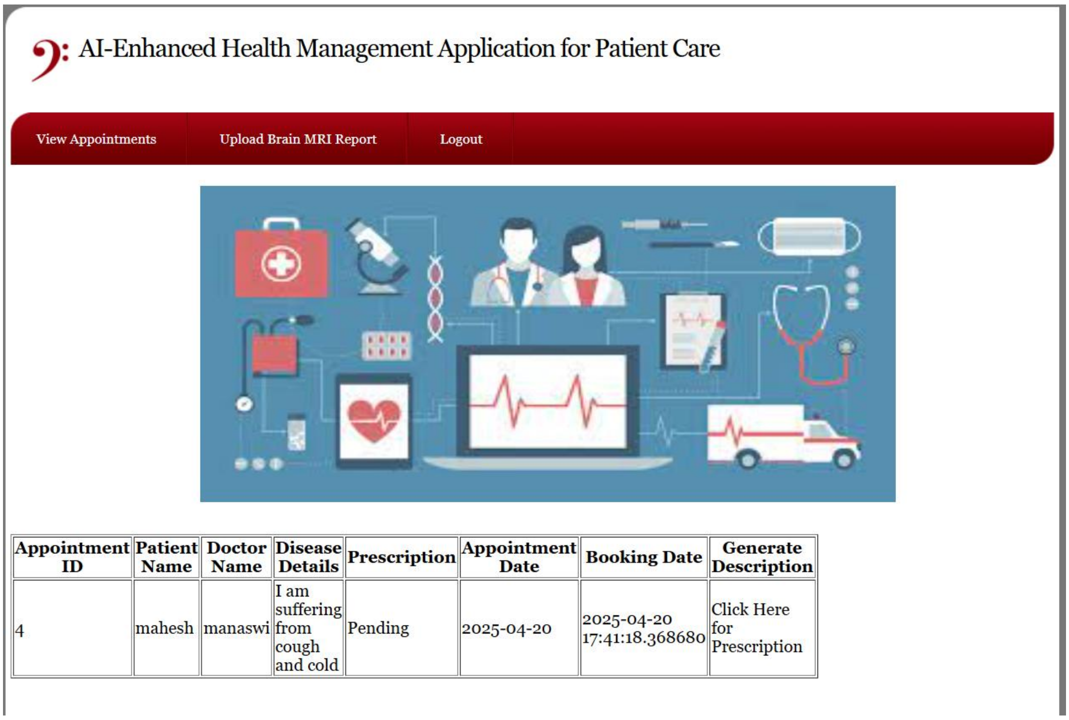
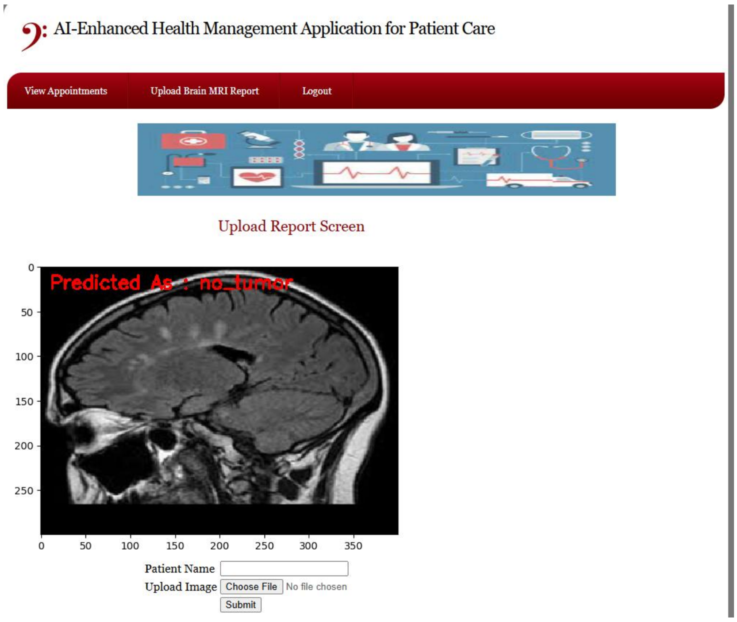


Fig. 5: View appointments page.

Table 1: Performance evaluation of existing and proposed models.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	76.13	75.21	73.86	73.88
CNN	99.30	99.22	99.41	99.31



(a)

(b)

Fig. 6: Sample predictions on uploaded MRI brain reports.(a) No tumor. (b) Meningioma tumor.

5. CONLUSION

This project presented an end-to-end web platform that integrates AI-driven brain-tumor detection with a full patient–doctor management workflow. Two machine-learning pipelines—a classical PCA + SVM approach and a deep-learning CNN—were benchmarked on the same MRI dataset. The PCA + SVM pipeline achieved an accuracy of 76.13 %, precision 75.21 %, recall 73.86 %, and F1-score 73.88 %, demonstrating reasonable—but limited—performance when compressing 3 072 features down to 300 principal components. In contrast, the CNN model delivered dramatically superior results, with 99.30 % accuracy, 99.22 % precision, 99.41 % recall, and 99.31 % F1-score, underscoring the power of convolutional feature extraction for medical-image classification. Beyond model performance, the Django-based interface seamlessly handles user registration, MRI upload and annotation, appointment booking, and prescription generation—providing a unified, auditable record for both patients and practitioners.

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