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Original Article

NeuroScanCare: Intelligent Brain Tumor Detection With Integrated Medical Support

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Abstract

Brain tumors represent a critical medical condition requiring prompt diagnosis and immediate access to specialized healthcare facilities. This research presents NeuroScanCare, an innovative integrated platform that combines artificial intelligence-based medical imaging analysis with intelligent healthcare navigation services.

The system employs a custom-designed Convolutional Neural Network (CNN) architecture featuring three convolutional layers, maxpooling operations, and dropout regularization to analyze uploaded MRI scans. Through comprehensive model evaluation, our custom CNN achieved superior performance with 84% classification accuracy, outperforming established architectures including VGG16 (80%), ResNet50 (78%), and InceptionV3 (70%). The model successfully categorizes brain scans into four distinct classifications: Glioma, Pituitary tumors, Meningioma, and non-tumor cases.

Upon tumor detection, the platform automatically activates its location-based recommendation engine utilizing the Geolocation API to determine user coordinates. The system implements the Haversine formula for precise distance calculations, identifying the five nearest healthcare facilities from the patient's current position. Each recommended hospital is presented with comprehensive details including specialization areas, patient ratings, supported insurance plans, contact information, and visual mapping integration.

The application leverages Flask framework for backend operations, HTML/CSS/JavaScript for user interface design, and Google Maps API for navigation services with multiple transportation options. Pandas library manages hospital database operations through CSV file handling.

NeuroScanCare bridges the gap between advanced medical diagnosis and accessible healthcare delivery, providing patients with immediate diagnostic insights coupled with actionable healthcare facility recommendations, ultimately enhancing clinical outcomes through timely medical intervention.

Introduction

The increasing prevalence of brain tumors has emphasized the urgent need for intelligent and automated diagnostic systems that support early detection and timely clinical intervention. This research introduces NeuroScanCare, a smart, integrated platform that combines deep learning-based brain tumor detection with a personalized hospital recommendation system. The system analyzes MRI scans using a custom-designed Convolutional Neural Network (CNN), classifying images into tumor and non-tumor categories. If a tumor is detected, the model further identifies its type—Glioma, Pituitary, or Meningioma—to aid clinical interpretation.

Several deep learning models were evaluated, including ResNet50, VGG16, InceptionNet, and a Custom CNN. Based on performance metrics such as accuracy and loss, the Custom CNN outperformed the others. Its architecture comprises multiple convolutional, pooling, dropout, and dense layers, ensuring robust feature extraction while minimizing overfitting.

Following tumor detection, the system retrieves the user's geolocation via the Geolocation API. Using the Haversine formula, it calculates distances to hospitals based on latitude and longitude, identifying the five nearest facilities. Each recommendation displays essential details, such as hospital name, specialization, address, rating, insurance coverage, contact email, and a representative image.

The system integrates Google Maps API to provide interactive maps with estimated travel times for walking, driving, or biking. Additional features like Street View, traffic layers, and custom overlays enhance user navigation.

The backend is developed using Python with Flask, while the frontend uses HTML, CSS, and JavaScript. Hospital data is managed using Pandas and stored in CSV format. This AI-driven, location-aware system provides a user-friendly solution that improves diagnostic

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precision and ensures timely access to healthcare.

Literature Survey

Avşar and Salcin [1] developed a method focused on the early detection of brain tumors using MRI imaging. Their approach involved isolating tumor-affected areas within brain scans and subsequently classifying the tumors into different categories. Recognizing the strong performance of deep learning in image classification tasks, they implemented a Convolutional Neural Network (CNN) model using the TensorFlow framework. The study demonstrated that their optimized CNN architecture achieved a significant classification accuracy of 91.66%, outperforming several prior techniques in both speed and precision.

Ranjbarzadeh et al. [2] introduced a robust and adaptable brain tumor segmentation technique that significantly enhances performance while reducing computational complexity. To address overfitting issues commonly seen in deep learning cascades, the authors designed a dual-path CNN architecture capable of extracting both fine-grained local features and broader global context. This architectural enhancement not only minimized training time but also delivered substantial improvements in segmentation accuracy. Their model achieved impressive average Dice similarity scores of 0.9203 for the whole tumor, 0.9113 for the tumor growth region, and 0.8726 for the tumor core—surpassing existing models in effectiveness.

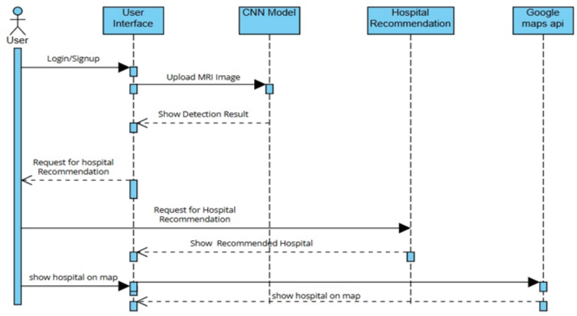
Kokila et al. [3] designed a comprehensive system for detecting brain tumors using MRI scans by addressing multiple classification tasks—such as identifying the presence, type, and location of the tumor—within a unified model. Rather than deploying separate models for each classification activity, the approach leveraged a multitask learning strategy using a single Convolutional Neural Network (CNN). This CNN model effectively managed tumor detection and classification while also estimating the tumor's spatial location. The proposed framework achieved a high detection accuracy of 92%, demonstrating its strength in handling complex brain MRI analysis through deep learning.

Sarkar et al. [4] introduced a method for classifying different types of brain tumors—specifically glioma, meningioma, and pituitary tumors—using MRI imaging and a two-dimensional Convolutional Neural Network (2D CNN). Their model was trained on a dataset comprising the most frequently occurring brain tumor categories. The proposed classification technique achieved a notable accuracy of 91.3%, showcasing its reliability in differentiating among the tumor types based on MRI features.

Gumaei et al. [5] proposed the use of a Regularized Extreme Learning Machine (RELM) model for brain tumor segmentation. To enhance the model's ability to process images effectively, a preprocessing stage was applied using the min-max normalization technique. This approach significantly improved the visual clarity of MRI images by adjusting brightness levels, thereby aiding the RELM model in achieving better interpretability and segmentation performance.

Kaplan et al. [6] introduced a dual-method approach for brain tumor classification and detection. The first technique, termed neighborhood-based Local Binary Pattern (nLBP), relied on distance relationships within the image, while the second utilized angular relationships between neighboring pixels. These preprocessing strategies were applied to MRI scans representing common tumor types, including glioma, meningioma, and pituitary tumors. The extracted statistical features from these enhanced images significantly improved character representation, enabling the model to surpass traditional feature extraction techniques in terms of performance and accuracy.

Working



The workflow of the NeuroScanCare system begins when the user logs in or signs up through the web-based user interface. After successful authentication, the user uploads an MRI brain scan image to the platform. This image is then sent to the trained Custom CNN model, which analyzes it to detect the presence of a tumor. If a tumor is found, the model further classifies it into one of the three types: Glioma, Meningioma, or Pituitary. The detection results are displayed to the user on the interface. If a tumor is confirmed, the user can request a hospital recommendation. The system uses the Geolocation API to retrieve the user's current coordinates and sends this location data to the hospital recommendation module. The module then applies the Haversine formula to calculate the distance between the user and hospitals in the dataset, identifying the top five nearest options. These recommended hospitals, along with detailed information such as name, address, specialization, distance, ratings, insurance support, and email contact, are shown to the user. If the user wishes to view the hospitals on a map, the system utilizes the Google Maps API to display their locations. Additional features such as estimated travel times, transportation modes, street view, traffic layers, and custom overlays enhance the user's ability to navigate and reach the selected healthcare facility efficiently.

Methodology

The NeuroScanCare system integrates deep learning for brain tumor detection with a location-based hospital recommendation module.

Initially, MRI brain images are preprocessed through normalization and data augmentation techniques such as rotation, flipping, and zooming to enhance model performance and prevent overfitting. These images are then input into a custom Convolutional Neural Network (CNN), consisting of convolutional, max-pooling, dropout, and dense layers. The CNN classifies scans into four categories: Glioma, Meningioma, Pituitary, or No Tumor, using softmax activation and categorical cross-entropy loss. Model performance is evaluated using accuracy scores, confusion matrices, and classification reports. Compared with pre-trained models like VGG16, ResNet50, and InceptionNet, the custom CNN demonstrated superior accuracy.

For hospital recommendations, the system captures the user's current location via the Geolocation API. The Haversine formula calculates the great-circle distance to each hospital in the dataset. The top five nearest hospitals are displayed, along with key details such as the hospital name, image, specialization, full address, rating, supported insurance schemes, official email, and distance.

Additionally, the Google Maps API is integrated to provide visual markers, estimated travel times, and directions for walking, biking, or driving. Advanced features like Street View, Traffic Layer, and Custom Overlays improve navigation and user experience.

The application is built using Python, Flask, Pandas, HTML, CSS, and JavaScript, ensuring efficient backend and frontend integration for real-time medical support.

Output Screenshots:-

Figure 1: Home Page of Brain Tumor Detection Web Application

This image illustrates the homepage of the NeuroScanCare system, a web-based platform for brain tumor detection. The user interface presents a clean and intuitive layout, featuring a central welcome message and a prominent "Check for Tumor" button. This call-to-action leads users to the diagnostic phase of the system. The branding in the top left corner clearly identifies the tool as "Brain Tumor Detector", while sign-in and sign-up options are available on the top right for user access control. The layout ensures ease of use and accessibility, encouraging user interaction from the start.

Figure 2: User Signup Interface for Secure Access

This screen represents the user signup module of the NeuroScanCare platform. It enables users to create an account by entering a username, email, and password, ensuring secure access and personalized interaction with the system. The simple and minimalistic design reduces user friction and facilitates quick registration. This feature supports data protection and session-based activity, which is essential in a medical application to maintain confidentiality and user accountability during MRI image uploads and result retrieval.

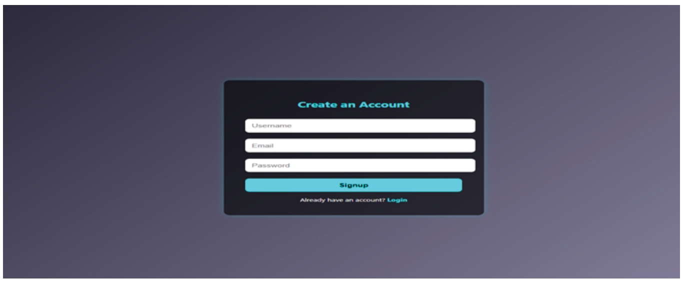


Figure 3: User Login Interface for Secure Session Management

This image depicts the login interface of the NeuroScanCare application. Registered users can securely access their personalized dashboard by entering their username and password. This form acts as a security layer, preventing unauthorized access and ensuring that only authenticated users can utilize sensitive medical features such as MRI analysis and hospital recommendations. The interface also provides a link to sign up for new users, ensuring seamless navigation between registration and authentication.

Figure 4: MRI Upload and Prediction Interface

This screen enables users to upload their MRI scan in image format and initiate the tumor detection process. The "Choose File" button allows for local file selection, while the "Predict" button submits the image to the backend. A custom Convolutional Neural Network (CNN) processes the input and predicts the presence of a brain tumor. This interface represents the core functionality of the system—bridging medical imaging with deep learning for real-time diagnostic assistance.

Figure 5: Prediction Result and Location-Based Hospital Recommendation

This screen shows the tumor prediction result after uploading an MRI scan. The system has detected a Glioma tumor with a confidence level of 79.33%. It briefly explains what Glioma is and includes a "Read More" link for further information. Below, there is a "Get Hospital Recommendations" button, which suggests nearby hospitals purely based on the user's current geolocation. The application uses the Geolocation API and Haversine formula to compute distances from the user's location to hospitals in the dataset.

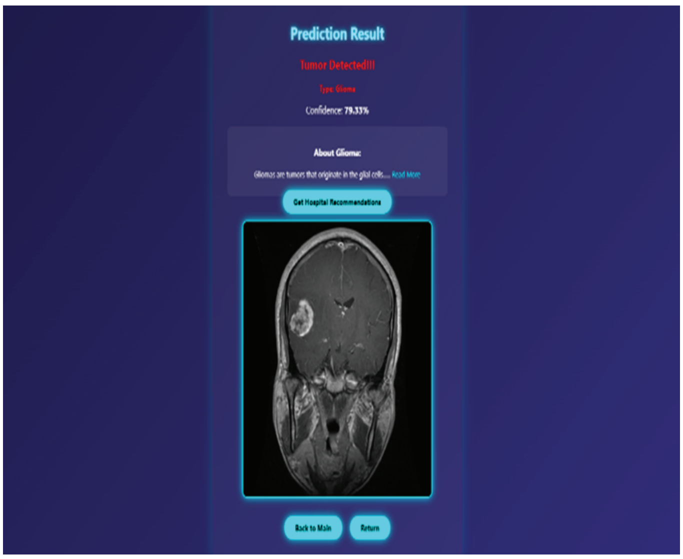


Figure 6: Hospital Recommendation – Get User Location

This interface welcomes the user to the Hospital Recommendation System and prompts them to click the "Get My Location" button. On clicking, the application uses the Geolocation API to capture the user's current latitude and longitude coordinates. These coordinates are later used to find and display nearby hospitals by computing the distance between the user and each hospital using the Haversine formula, ensuring recommendations are purely based on proximity.

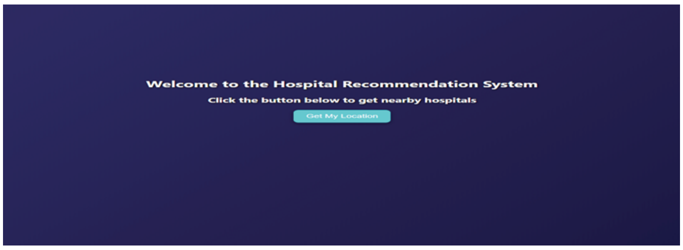


Figure 7: Nearby Hospital Recommendations Based on Location

This screen displays a list of recommended hospitals near the user's current location, calculated using the Haversine formula. Each hospital entry includes:

- Hospital Name and Image
- Specialty (e.g., Neurosurgery Oncology)
- Address
- Rating (from Google or patient feedback)
- Email
- Distance from current location
- Accepted insurance schemes
- Cashless treatment availability
- A "Show on Map" button for directions

Hospitals are sorted by proximity, enabling users to quickly access the nearest and most suitable medical centers.

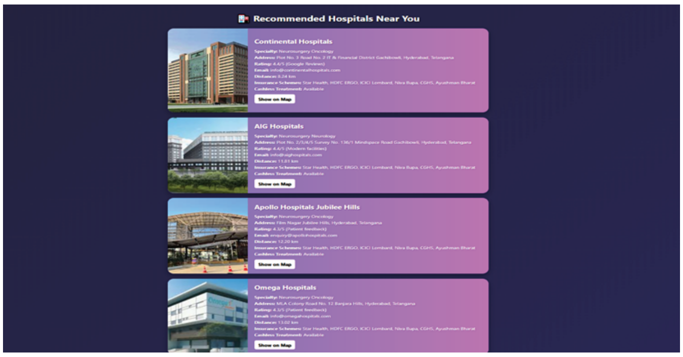


Figure 8: Google Maps Integration for Hospital Location

This figure shows the Google Maps interface opened via the "Show on Map" button from the hospital recommendation page. The selected hospital—AIG Hospitals—is marked with a red location pin. The satellite view enables users to clearly see the building structure, surroundings, and nearby medical facilities.

This integration helps users:

- Visually identify the exact hospital location.
- Navigate with precision using built-in Google Maps features.
- Access additional details like directions, reviews, and nearby amenities.

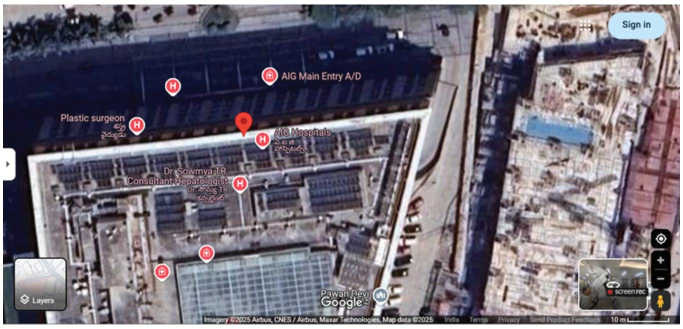


Figure 9: Model Comparison for Brain Tumor Detection

This figure presents the comparative analysis of four deep learning models used for brain tumor classification: InceptionV3, ResNet, VGG16, and a Custom CNN. Each model's classification report and training vs. validation accuracy graph are shown.

Model Accuracies:

- InceptionV3: 70%
- ResNet: 78%
- VGG16: 80%
- Custom CNN: 84%

The Custom CNN achieved the highest accuracy, demonstrating better generalization for the dataset used. The accuracy and F1-scores indicate its superior performance across tumor classes (glioma, meningioma, pituitary).

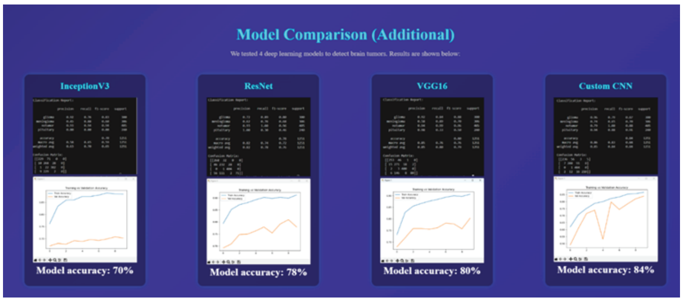
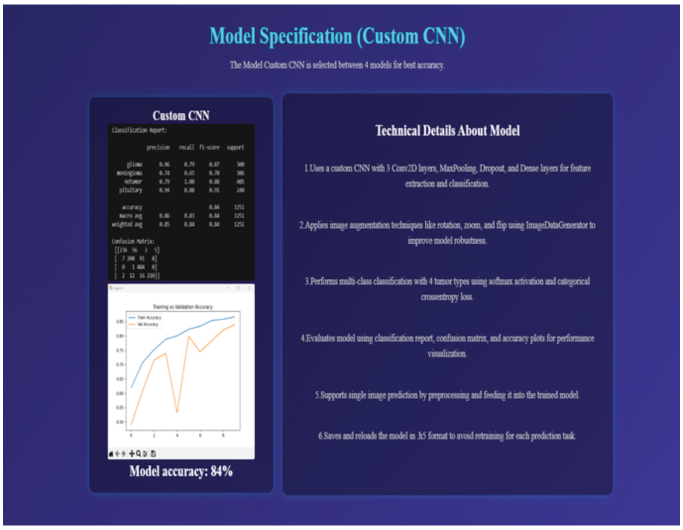


Figure 10:- Selected Model Analysis CustomCNN

This page presents the Custom CNN model, selected for its highest accuracy (84%) in brain tumor classification among four tested models. It uses 3 Conv2D layers, MaxPooling, Dropout, and Dense layers for effective feature extraction. Image augmentation enhances model robustness. The model performs multi-class classification across four tumor types using softmax activation. Evaluation includes precision, recall, F1-score, a confusion matrix, and accuracy plots. It supports single image predictions and saves the model in .h5 format for reuse. Overall, the Custom CNN balances performance and efficiency, making it ideal for accurate brain tumor detection.



Conclusion

The proposed NeuroScanCare system effectively combines deep learning and location-based services to deliver an intelligent, end-to-end solution for brain tumor detection and hospital recommendation. By utilizing MRI scans and a custom Convolutional Neural Network (CNN), the system achieves high accuracy in classifying brain tumors and identifying specific types, including Glioma, Meningioma, and Pituitary tumors. Its performance, validated against widely used architectures such as VGG16, ResNet50, and InceptionV3, demonstrates strong robustness and reliability for medical diagnostic applications.

Beyond detection, the system integrates geolocation and the Haversine algorithm to provide accurate and personalized hospital recommendations. By considering factors such as distance, specialization, hospital ratings, and insurance coverage, the platform not only assists in diagnosis but also improves access to suitable healthcare services. Features like Google Maps integration, estimated travel times, and interactive hospital profiles enhance user experience and accessibility.

Developed using Flask, Python, Pandas, and modern web technologies, NeuroScanCare illustrates how artificial intelligence can bridge the gap between early diagnosis and timely medical intervention. The system has significant potential in real-world healthcare environments, enabling faster clinical decisions and improving outcomes for patients with brain tumors.

Future Scope

NeuroScanCare offers a solid foundation for intelligent healthcare solutions, with promising avenues for future development. Enhancing the system with advanced deep learning models—such as attention-based CNNs or Transformer architectures—can improve tumor detection accuracy across varied MRI datasets.

Integrating real-time data from wearable health devices can enable continuous patient monitoring and proactive care. The hospital recommendation module can be expanded to include features like doctor availability, appointment booking, patient reviews, and multilingual support for broader accessibility.

Connecting the system with Electronic Health Records (EHRs) would streamline data sharing and enhance coordination among healthcare providers. Additionally, deploying NeuroScanCare on mobile platforms or integrating it into telemedicine apps can extend its impact to rural and underserved communities.

Adopting federated learning would further strengthen data privacy while enabling collaborative model training across institutions.

In summary, NeuroScanCare holds significant potential to evolve into a robust, AI-driven healthcare assistant for early, accurate, and accessible brain tumor diagnosis and support.

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