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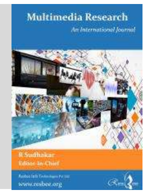

Quick Care: AI-Powered Healthcare for Accessible Diagnostics and Community Wellness

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Abstract: The study introduces a cohesive, AI-powered healthcare platform aimed at overcoming the shortcomings of current systems in early disease detection, tailored healthcare suggestions, and access to resources. We have created three main models: a Brain MRI Tumour Detection model, a Pneumonia Detection model for chest X-rays, and a Symptom Prediction model that employs decision trees and support vector machines (SVM) to forecast diseases from user-reported symptoms. These models together increase diagnostic precision, strengthen patient-physician communication, and encourage prompt intervention. In contrast to traditional systems, our platform combines a strong appointment scheduling feature with a distinctive community-focused donation system for non-monetary contributions such as blood and organ donations. The models were developed using various datasets, attaining high accuracy levels (exceeding 93%) by employing methods such as data augmentation and hyperparameter tuning. Our solution includes a healthcare chatbot for instant patient inquiries, guaranteeing an interactive and comprehensive user experience. A comparative analysis with current solutions showed that our platform lowers false negatives and shortens diagnostic delays, especially in urgent situations. The unification of diagnostic, preventive, and supportive healthcare services into one platform provides a scalable and affordable option for enhancing healthcare access, particularly in underprivileged areas. This study shows the ability to merge AI and community assets to transform healthcare provision, guaranteeing prompt diagnosis, individualized treatment, and improved patient results.

Keywords: AI in Healthcare, Brain MRI Tumor Detection, Pneumonia Detection, Symptom Prediction, Digital Healthcare Platform.

Nomenclature

Abbreviation	Full Form
AI	Artificial Intelligence
SVM	Support Vector Machines
CNN	Convolutional Neural Network
NLP	Natural Language Processing
ML	Machine Learning
MRI	Magnetic Resonance Imaging
CT	Computed Tomography

1. Introduction

Providing accessible and timely medical care remains a significant challenge, especially in underserved regions. High costs, limited resources [1, 2], and inadequate infrastructure delay diagnoses [3, 4] for critical conditions like brain tumors and pneumonia. These issues are compounded in rural areas [6], where access to diagnostic tools and specialists is minimal, leading to worsening health outcomes and preventable fatalities. Furthermore, communication gaps between patients and healthcare providers hinder effective health management. Fragmentation in existing healthcare solutions exacerbates these problems [4]. Platforms such as WebMD and Healthline offer basic symptom checkers, while telemedicine services like Practo and Zocdoc facilitate consultations [1,10]. However, these systems lack integration with advanced diagnostic tools or community engagement features. Moreover, reliance on internet connectivity excludes patients in remote areas, highlighting the need for a comprehensive, unified digital healthcare solution.

To tackle these challenges, we introduce an AI-powered healthcare platform integrating advanced diagnostics [3, 5], personalized symptom analysis, and community-focused features [5, 6]. The platform's core components include diagnostic models utilizing CNNs for Brain MRI Tumor Detection and Pneumonia Detection with over 93% accuracy, symptom prediction employing a hybrid approach with Decision Trees and Support Vector Machines (SVM) for accurate disease prediction, a healthcare chatbot leveraging Natural Language Processing (NLP) to provide real-time support and guidance [8, 9], appointment scheduling [7] facilitating seamless booking with healthcare providers and a community donation system enabling geolocation-based coordination for blood and organ donations. This integrated platform offers a user-friendly interface that improves accessibility and efficiency, particularly for underserved populations [7]. The main contributions of the project are

1. Developing a Brain MRI Tumor Detection and Pneumonia Detection, enhancing the precision of disease prediction.
2. Introducing an AI chatbot and scheduling system to streamline patient-doctor interactions and improve healthcare efficiency [10, 11, 14].
3. Implementing a donation system to facilitate and raise awareness for life-saving contributions such as blood and organ donations [12, 13].

The platform demonstrates measurable advancements in healthcare delivery and outcomes. Brain MRI Tumor Detection achieved 95.8% accuracy, while Pneumonia Detection attained 93.7% accuracy. The chatbot and scheduling system reduce diagnostic delays and enhance user experience. The donation system facilitates life-saving contributions and raises awareness, and the AI models are adaptable to diverse medical datasets and conditions. By integrating diagnostics, prevention, and community engagement, this platform establishes a holistic healthcare ecosystem that prioritizes improved patient outcomes and collective well-being.

The rest of the manuscript is organized as follows: Section 2 covers the literature. Section 3 details the methodology, presenting the development and integration of AI-powered models. The results and discussion are emphasized in Section 4, Section 5 explains the advantages and the disadvantages of the method, and Section 6 summarizes the key outcomes and future work directions in the conclusion.

2. Literature Review

The rapid growth of digital healthcare solutions has introduced a variety of tools, such as symptom checkers, telemedicine platforms, and diagnostic applications. However, these models often operate in silos, providing isolated services without offering a comprehensive healthcare solution. Symptom checkers like those from WebMD [1] [10] or Healthline provide generalized results but lack localized doctor recommendations or integration with diagnostic tools. Telemedicine platforms such as Practo and Zocdoc focus primarily on connecting patients to doctors but do not offer diagnostic capabilities for medical imaging or report analysis. Diagnostic applications, on the other hand, specialize in specific conditions but often require separate installations, making the healthcare journey fragmented and inefficient. These solutions rarely address the need for non-monetary healthcare contributions, such as blood and organ donations, which play a critical role in emergency care [12] [13].

The platform seeks to bridge these gaps by offering an integrated, patient-centric solution. It combines AI-driven symptom analysis, medical diagnostics, personalized doctor recommendations, and a healthcare chatbot within a single interface. Moreover, the inclusion of a community-focused donation system promotes a holistic approach to healthcare. By providing a unified and accessible platform, we aim to streamline the healthcare experience and foster community involvement, thus addressing the limitations of existing models.

3. Methodology

Our platform integrates a scheduling system to book appointments with doctors and track donations to provide a seamless user experience for individuals. Initially, the symptom prediction module evaluates initial symptoms and suggests potential conditions or if a medical image is uploaded, it is processed by the respective model (Brain MRI or Pneumonia Detection). Then the diagnosis results are routed to the chatbot, which provides immediate recommendations and facilitates scheduling a consultation.

The donation system enables users to locate and participate in nearby blood or organ donation drives, synchronized with the patient's geolocation.

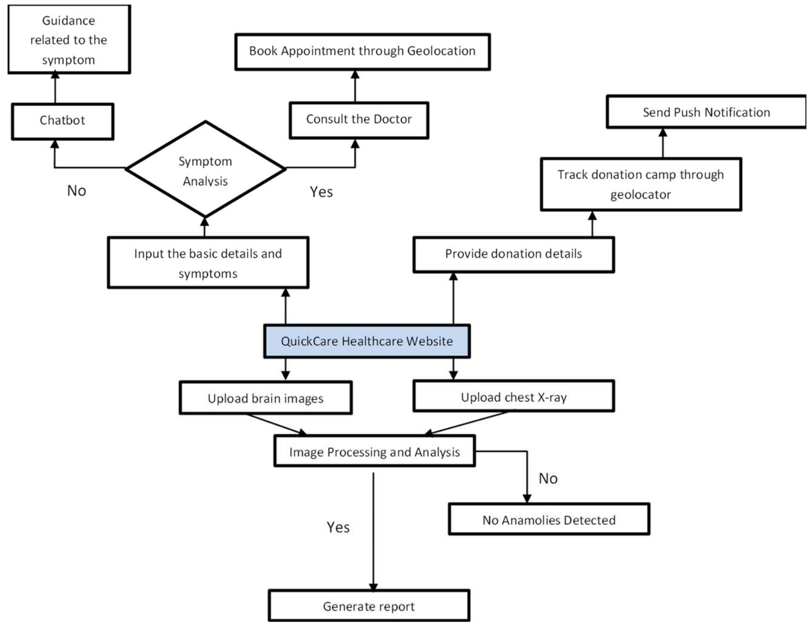

Fig 1. *Overall proposed method*

The project leverages advanced AI and web development techniques to create an integrated healthcare platform that addresses multiple facets of patient care. Here's how each methodology was applied:

Symptom Analysis and Healthcare Chatbot

The model was trained on a large dataset containing various symptoms and their associated conditions. Users input their symptoms through a user-friendly interface, and the system analyzes the data to provide details of the potential health conditions along with guidance on whether a doctor's consultation is necessary. It is implemented through an AI-based model using supervised learning and NLP techniques. This component ensures early detection and timely advice, reducing the risk of disease progression. To offer continuous support and integration of a healthcare chatbot powered by NLP. The chatbot is designed to handle general health inquiries, provide symptom-related advice, and guide users through the platform's various features. By offering instant responses, the chatbot improves user engagement and reduces the need for direct human intervention for routine queries. If the doctor consultation is necessary then using geolocation services, the platform suggests healthcare professionals in the patient's vicinity. The system integrates user preferences, such as specialization, ratings, and distance, to personalize doctor recommendations. Developed an appointment booking system that syncs with doctors' real-time availability. Users can select their preferred healthcare provider and schedule appointments directly through the platform.

Medical Report Scanning

For diagnostic purposes, developed CNNs capable of analyzing medical images for specific conditions such as brain tumors, pneumonia, and X-ray abnormalities. These models were trained on publicly available datasets and fine-tuned using transfer learning to achieve high accuracy. Users can upload their medical reports, and the system provides a detailed analysis within seconds, enabling quicker diagnoses and facilitating better decision-making for both patients and doctors.

Donation System

To foster community involvement, implementation of a donation system that informs users about nearby non-monetary donation drives, such as blood and organ donation camps. This system uses geolocation and push notifications to encourage participation, enabling users to contribute to critical healthcare resources in their community.

3.1 Brain Tumor Detection Model

The process starts with uploading the brain scan report to a website. The uploaded data is then preprocessed to clean and prepare it for analysis. Next, the data is analyzed using a CNN model optimized with the Adam algorithm to improve accuracy and performance. Parameters are assigned, and the model undergoes training and testing to learn and evaluate its performance. The training and validation results are visualized over multiple cycles (epochs) to monitor progress. Finally, the model outputs the test results, including loss (error rate) and accuracy, to indicate how well it detected the brain tumor.

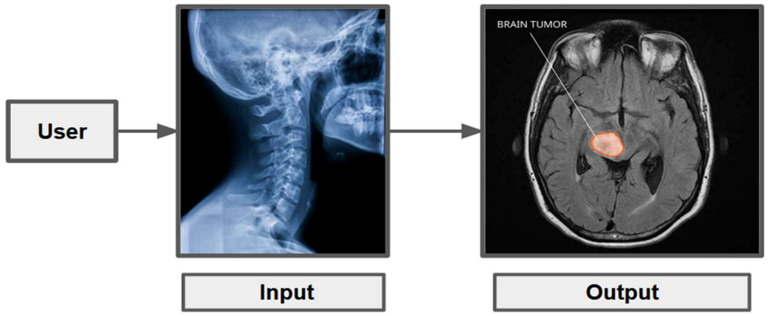

Fig. 2. *Brain Tumor Detection*

Algorithm for Brain Tumor Detection Model

Import Libraries
- Load all necessary libraries for handling images, building and training the model, and evaluating its performance.

Download and Load Dataset
- Use kagglehub to download the dataset.
- Load images and their labels from the dataset directory.

Pre-process Data
- Resize all images to a uniform size of 128x128 pixels.
- Normalize pixel values to the range [0, 1].
- Split data into training and testing sets.

Define Model Architecture
- Create a CNN model with the following layers:
  - Add a convolutional layer with 32 filters and a (3x3) kernel.
  - Add a max-pooling layer with a (2x2) pool size.
  - Add another convolutional layer with 64 filters and a (3x3) kernel.
  - Add a max-pooling layer with a (2x2) pool size.
  - Add another convolutional layer with 128 filters and a (3x3) kernel.
  - Add a max-pooling layer with a (2x2) pool size.
  - Flatten the output and add a dense layer with 128 units.
  - Add a dropout layer with a 50% dropout rate.
  - Add a final dense layer with 1 unit and sigmoid activation for binary classification.

Compile the Model
- Set the optimizer to Adam.
- Use binary cross-entropy as the loss function.
- Set accuracy as the evaluation metric.

Define Early Stopping
- Create a callback to stop training once accuracy exceeds 99%.

Train the Model
- Train the model using the training data, with a 20% validation split.
- Use the early stopping callback to halt training when desired accuracy is achieved.

Evaluate the Model
- Test the model on the test set to determine its accuracy and loss.

Display Results
- Print test results for loss and accuracy.
- Visualize training and validation performance over epochs.

End of Algorithm

Fig 3: Algorithm of the Brain Tumour Detection

3.2 Pneumonia Detection Model

The process for pneumonia detection begins with uploading a chest X-ray image to a website. Once uploaded, the image is preprocessed to enhance quality and prepare it for analysis, including resizing, normalization, and augmentation. The preprocessed image is then analyzed using a CNN model, which is optimized with the Adam optimizer for efficient learning. Parameters such as learning rate, batch size, and epochs are assigned to train the model. The training and validation performance is monitored and visualized over multiple epochs to evaluate progress. Finally, the trained model is tested on a separate dataset, and the results, including test loss and accuracy, are printed to assess its effectiveness in detecting pneumonia.

Algorithm for Pneumonia Detection Model

Import Necessary Libraries
Import libraries for handling data, preprocessing images, and building deep learning models.
Download Dataset
Use a dataset repository to download a chest X-ray dataset for pneumonia detection.
Set Dataset Paths
Define paths for training, testing, and validation datasets for organized access.
Preprocess Data Using Image Augmentation
Apply rescaling to normalize pixel values.
Use data augmentation techniques such as rotation, width and height shifts, shear, zoom, and horizontal flipping to increase dataset variability.
Create a training data generator with these augmentations and a test data generator with only rescaling.
Define Model Architecture
Build a CNN with multiple layers:
Convolutional layers with increasing filter sizes for feature extraction.
Max pooling layers to reduce dimensionality and retain significant features.
Flatten layer to convert 2D feature maps into a 1D vector.
Fully connected dense layers for decision-making.
Dropout layer to prevent overfitting.
Sigmoid activation function in the final dense layer for binary classification (pneumonia or not).
Compile the Model
Use the Adam optimizer for adaptive learning.
Set binary cross-entropy as the loss function since it is a binary classification problem.
Use accuracy as the evaluation metric.

Implement Early Stopping
Define an early stopping mechanism to stop training if validation loss stops improving for a set number of epochs.
Train the Model
Train the model on the augmented training data.
Use validation data to monitor the model's performance during training.
Evaluate the Model
Test the model using unseen data (test set) to evaluate its performance.
Calculate and display the model's accuracy and loss on the test set.

Visualize Results (Optional)
Plot training and validation accuracy/loss curves to assess model performance over epochs.
End of Algorithm

Fig 4: Algorithm for Pneumonia Detection Model

4. Result and Discussion

4.1 Dataset

To achieve accurate results for our healthcare project, we adopted a multi-faceted approach using three distinct models: Symptom Detection, Brain tumor, and pneumonia detection and donation system. Each model was developed with specific datasets tailored to the respective medical condition, ensuring high relevance and performance.

- Tumor Detection Model was trained on MRI scans from the "Brain MRI Images for Brain Tumor Detection" dataset.
- Pneumonia Detection Model used the "Chest X-Ray Images for Pneumonia" dataset.

4.2 Website

The datasets were chosen for their quality, size, and comprehensiveness, ensuring that the models could generalize well across varied cases.

The Fig. 3 depicts the homepage of QuickCare, a healthcare platform designed to simplify medical record management and access to healthcare services. The platform offers a user-friendly interface with a prominent "Get Started" button, inviting users to explore its features. Key services include scanning and uploading medical reports, viewing basic health insights derived from these reports, and booking appointments with healthcare professionals. By consolidating these essential features, QuickCare aims to empower individuals to take control of their health by providing convenient access to their medical information and facilitating seamless interaction with healthcare providers.

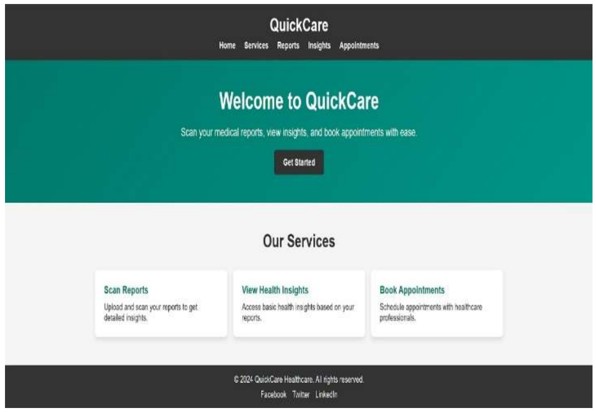

Fig. 3. *Website Page*

4.3 Value Selection and Parameter Tuning

Key hyperparameters were carefully selected to balance model complexity and performance

Tumour Detection and Pneumonia Detection Models

- Batch Size: 32 to maintain computational efficiency and generalization.
- Learning Rate: Optimized using Adam to ensure convergence.
- Dropout Rate: Set to 0.5 to mitigate overfitting.

Symptom Prediction Model

- Decision Tree Depth: Tuned to avoid overfitting while maintaining interpretability.
- SVM Kernel: Linear kernel is chosen for simplicity and speed.

These values were fine-tuned through cross-validation to achieve optimal accuracy while minimizing overfitting.

4.4 Numerical Analysis

The performance of the brain tumor detection model is evaluated based on its accuracy across training, validation, and test datasets. The model achieved a high training accuracy of 98.5%, indicating that it has learned the patterns within the training data effectively. The validation accuracy, slightly lower at 96.2%, demonstrates the model's ability to generalize to unseen data during training, showing minimal overfitting. The test accuracy, recorded at 95.8%, reflects the model's performance on entirely new data and suggests reliable real-world applicability. The close alignment between validation and test accuracy confirms that the model generalizes well, maintaining robust performance across datasets.

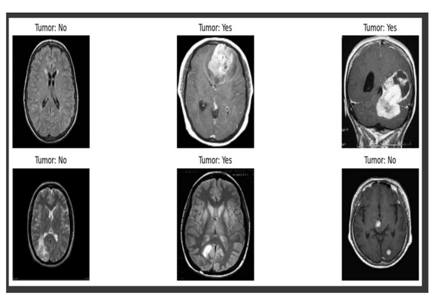

Fig. 4. *Dataset and Output of Tumour Detection Model*

The pneumonia detection model demonstrates strong performance across training, validation, and test datasets, with a training accuracy of 97.1%. This high value indicates that the model has effectively learned patterns from the training data. The validation accuracy of 94.5% shows the model's ability to generalize to unseen data during the training phase, with some minor drops compared to training accuracy, suggesting minimal overfitting. The test accuracy of 93.7% reflects the model's performance on completely new data, showcasing its reliability in practical applications. The consistent drop from training to validation and test accuracy indicates a well-optimized model with good generalization, suitable for real-world pneumonia detection tasks.

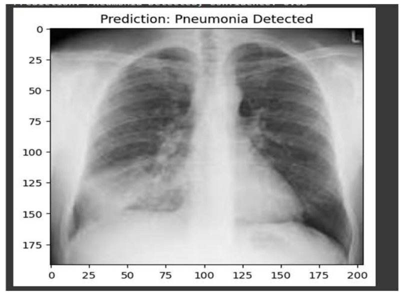

Fig. 5. *Output for Pneumonia Detection Model*

The symptom-based disease prediction model was evaluated using two different algorithms: Decision Tree and SVM. The Decision Tree model achieved an accuracy of 92.4%, demonstrating its ability to effectively classify diseases based on symptoms with a relatively high success rate. However, the SVM model outperformed the Decision Tree, achieving a higher accuracy of 94.1%. This suggests that SVM's ability to handle complex relationships and boundaries between classes makes it more effective for this prediction task. The comparison highlights the strength of SVM in achieving more precise predictions, making it a preferred choice for symptom-based disease prediction scenarios. The integration of machine learning models such as CNNs and SVM with NLP chatbot assistance provides a scalable framework for future studies.

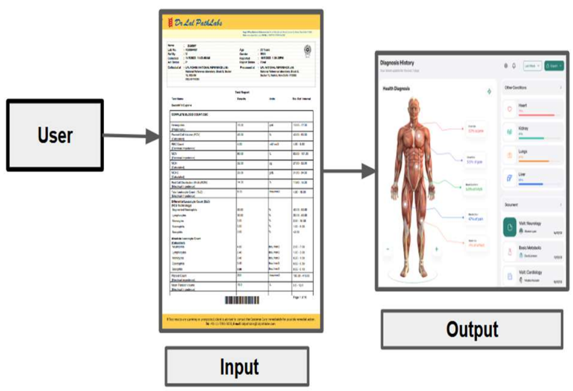

Fig. 6. *Disease Prediction Model*

5. Advantages and Disadvantages

Advantages:

- High diagnostic precision across tasks.
- Integration of donation and scheduling features.

Disadvantages:

- Dependence on robust datasets.
- Limited functionality in regions with unreliable internet.

6. Conclusion

In conclusion, this research introduces a comprehensive AI-powered healthcare platform that integrates high-accuracy diagnostic models, symptom analysis, and community-centric features to address critical healthcare challenges. Key contributions include achieving robust performance in disease detection (e.g., 95.8% test accuracy for brain tumor detection and 94.1% for symptom-based disease prediction using SVM) while optimizing hyperparameters and leveraging data augmentation to enhance model robustness. The platform fosters accessibility and community engagement through features like scheduling, donation systems, and an NLP-enabled chatbot for health queries. These innovations address diagnostic delays, improve resource allocation, and offer scalable, affordable solutions for underserved areas. Future work will expand disease coverage, improve offline functionality, and enhance the system's economic viability, paving the way for impactful, community-driven healthcare advancements.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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