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Brain Hemorrhage Detection Using CNN

Dr. Arun Singh Chouhan, M Rakesh Reddy, K Sarath Chandra, A Shivasai, A Sai Teja Reddy

Associate Professor, Malla Reddy University, Maisammaguda, Hyderabad, India

B. Tech, Department of CSE Malla Reddy University, Maisammaguda, Hyderabad, India

B. Tech, Department of CSE Malla Reddy University, Maisammaguda, Hyderabad, India

B. Tech, Department of CSE Malla Reddy University, Maisammaguda, Hyderabad, India

B. Tech, Department of CSE Malla Reddy University, Maisammaguda, Hyderabad, India

ABSTRACT*:* A brain hemorrhage, or brain bleed, is bleeding in or around brain tissue and an emergency to treat. This project improves diagnostic effectiveness by automatically detecting hemorrhage with deep learning and adds an intuitive interface to enhance interaction between radiologists, physicians, and non-professionals. Current diagnostic systems have not been easy to use with an intuitive interface, thus restricting use by non-professionals. To fill this gap, we created a CNN-based system with an interactive platform for smooth communication between medical professionals and the public. The CNN model showed high sensitivity and specificity in detecting hemorrhage, consistent with previous studies. The user interface was usability-tested and accessible, with positive feedback from medical professionals and patients. This integration increases user interaction and understanding, making AI-based diagnosis more efficient. Through the integration of deep learning and user-friendly interface, this system accelerates diagnostics, minimizes radiologists workload, and enhances patient interaction. The project is adding to AI-led healthcare innovation by making scalable solutions for vital diagnostics possible while encouraging improved communication among healthcare professionals and patients.

KEYWORDS: Brain Hemorrhage, Brain Bleed, Computed Tomography (CT) Scan, Convolutional Neural Network (CNN), Healthcare, Flask, ReactJS, SQLite

I. INTRODUCTION

A hemorrhage of the brain is a life-threatening illness resulting from bleeding within or around the brain and necessitates immediate diagnosis. Computed Tomography (CT) scans are the first imaging technique used in detection, though it is a time-consuming manual interpretation that is medical expert-reliant[13]. Artificial intelligence-based techniques, especially Convolutional Neural Networks (CNNs), have immensely enhanced hemorrhage detection rates[9]. Experiments have employed segmentation methods such as Otsu's thresholding and Grad-CAM visualization to improve localization [2,7]. Despite the improvements, most work is aimed at algorithmic correctness instead of usability, which limits AI-based diagnosis to experts [18]. The gap in the research is not having an interactive interface where the radiologist as well as a non-medical user can simply interpret the result of AI. Current systems do not cater to easy communication between healthcare professionals and the public.

To solve this, we implemented a CNN-based system for hemorrhage detection with an interactive user interface. It combines real-time AI feedback, visual explanations, and interactive features to help both specialists and lay users. This solution lightens radiologists' workload while enhancing diagnostic efficiency. The research is centered on CT-based hemorrhage detection and usability testing, adding to AI-powered healthcare innovation and enabling critical diagnostics to be made more accessible.

II. LITERATURE REVIEW

Brain hemorrhage detection is crucial for timely diagnosis and treatment. Traditional manual interpretation of CT scans is time-consuming and prone to errors, necessitating the use of AI-driven approaches for automated detection. Deep learning models, especially CNN-based architectures, have demonstrated significant potential in improving classification accuracy [1,5].

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Early approaches relied on feature-based classification, using handcrafted features extracted from ROI-based segmentation [2]. However, with the advent of deep learning, models such as LeNet, GoogLeNet, and Inception-ResNet improved detection accuracy [9]. Some studies incorporated hybrid models combining CNN with LSTM for enhanced performance [17].

Several works used pretrained deep learning models, such as ResNet101-V2 and Inception-V4, to extract meaningful features [11]. Additionally, genetic algorithm-based feature selection helped refine classification results, boosting F1-score by 7.38% over traditional methods [2]. or segmentation, methods like Otsu's thresholding, fuzzy clustering, and Grad-CAM visualization enabled better localization of hemorrhage regions [4,7]. Adaptive denoising techniques, such as curvelet transform and total variation methods, further enhanced image clarity [20]. Studies show that AI-assisted radiology models outperform human experts, achieving 92-99% accuracy in detecting and classifying hemorrhages [10,12]. However, challenges remain, including limited labeled datasets, computational constraints, and lack of real-time deployment [18].

Future research should focus on developing an intuitive interface that facilitates AI-assisted hemorrhage detection for both radiologists and non-medical experts. Integrating visual explanations, interactive tools, and real-time AI feedback will enhance usability and ensure broader adoption in clinical and remote healthcare settings.

III. METHODOLOGY

A. Materials Used

This research employs a dataset of Brain CT scan images classified into two classes: Hemorrhage and Normal. The programming implementation was done using Python, with libraries including TensorFlow, Keras, NumPy, Pandas, OpenCV, Seaborn, and Matplotlib. TensorFlow and Keras were used for model training, while ReactJS was employed for the frontend, Flask for API integration, and SQLite as the backend database. The training was speeded up by utilizing an NVIDIA GPU, while testing and assessment were performed on an Intel-based CPU. The development cycle was handled with the help of Jupyter Notebook.

Fig.1 CT Scan Indicating Hemorrhage

B. Data Collection & Preprocessing

The preprocessing and data collection step was done by loading Brain CT images from the directory of the dataset and marking them according to their respective classes, which could be Hemorrhage or Normal. The images were first

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converted into grayscale and resized into a single dimension of 256×256 pixels. For better generalization of the model, rescaling, flipping, and rotation were performed with the help of ImageDataGenerator as data augmentation methods. The data was then divided into training and testing data as 90% and 10% and further split the training data into 80% training and 20% validation sets to improve model performance.

Fig.2 CT Scan Without Hemorrhage

C. Model Development (CNN Architecture)

A five-layered Convolutional Neural Network (CNN) was trained for classification. The model had several Conv2D layers combined to extract informative features from the images, followed by the use of BatchNormalization and Dropout layers for evading overfitting. MaxPooling2D was used to shrink dimension while retaining important information. The Flatten and Dense layers classified the extracted features, with the last layer employing a Softmax activation function in order to classify images into Hemorrhage or Normal. The model was then compiled with the Adam optimizer and categorical cross-entropy loss function in order to ensure proper training and convergence.

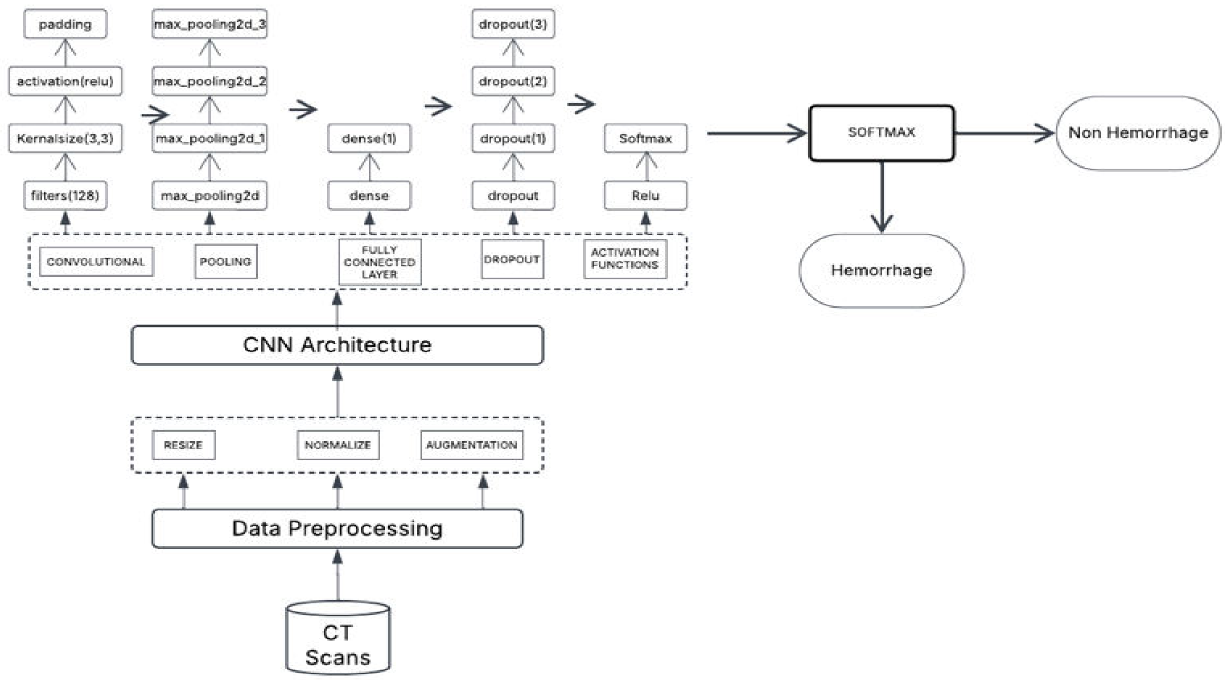

Fig.3 CNN Architecture

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D. Explanation

The above Fig.3 represents a CNN architecture for hemorrhage detection using CT scans. It consists of three main stages: Data Preprocessing, CNN Architecture, and Classification. In the Data Preprocessing stage, CT scan images undergo several transformations to ensure they are suitable for model training. This includes resizing images to a fixed dimension, normalizing pixel values to bring them into a standard range for better training stability, and applying data augmentation techniques such as rotation, flipping, and zooming to enhance dataset variability and improve model generalization.

The CNN Architecture consists of multiple layers designed to extract meaningful features from input images. The Convolutional layer applies 128 filters with a kernel size of (3,3) to detect patterns in the image. The ReLU activation function introduces non-linearity, while padding ensures that spatial dimensions are maintained. The Pooling layers, including max pooling with different sizes (2×2, 1×1, 2×2, 3×3), help reduce the feature map dimensions while retaining essential information. After feature extraction, the Fully Connected Layer processes high-level features for classification. To prevent overfitting, Dropout Layers are incorporated at multiple stages, progressively removing neurons during training. The final Activation Function applies a Softmax function, which outputs probability scores for classification.

In the Classification stage, the model's Softmax output determines whether a given CT scan indicates hemorrhage or not. If the probability is higher for hemorrhage, the model classifies it as "Hemorrhage"; otherwise, it is classified as "Non-Hemorrhage." This structured approach ensures effective feature extraction, dimensionality reduction, and accurate classification, making the model robust for hemorrhage detection.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 254, 254, 12)	120
batch_normalization (BatchNormalization)	(None, 254, 254, 12)	48
max_pooling2d (MaxPooling2D)	(None, 127, 127, 12)	0
conv2d_1 (Conv2D)	(None, 127, 127, 24)	2,616
dropout (Dropout)	(None, 127, 127, 24)	0
max_pooling2d_1 (MaxPooling2D)	(None, 63, 63, 24)	0
conv2d_2 (Conv2D)	(None, 63, 63, 64)	13,888
dropout_1 (Dropout)	(None, 63, 63, 64)	0
max_pooling2d_2 (MaxPooling2D)	(None, 31, 31, 64)	0
conv2d_3 (Conv2D)	(None, 31, 31, 128)	73,856
dropout_2 (Dropout)	(None, 31, 31, 128)	0
max_pooling2d_3 (MaxPooling2D)	(None, 15, 15, 128)	0
conv2d_4 (Conv2D)	(None, 15, 15, 128)	147,584
dropout_3 (Dropout)	(None, 15, 15, 128)	0
max_pooling2d_4 (MaxPooling2D)	(None, 7, 7, 128)	0
flatten (Flatten)	(None, 6272)	0
dense (Dense)	(None, 512)	3,211,776
dropout_4 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 2)	1,026

Table1: CNN Model Summary

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D.Training & Evaluation

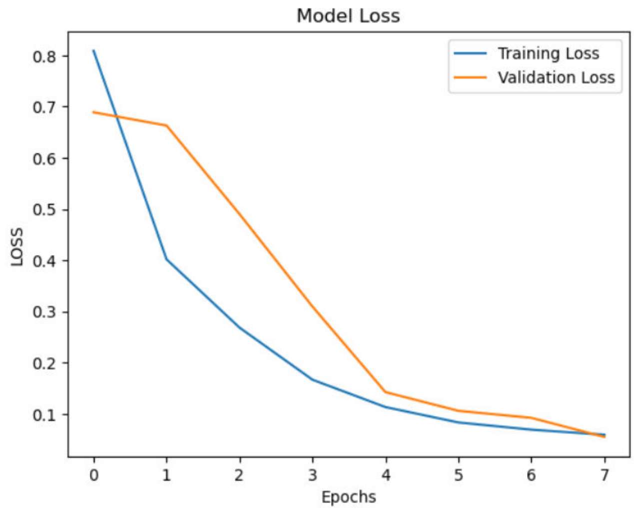

Fig.4 Model Loss

The CNN model was trained on eight epochs via the model.fit() function with an Early Stopping mechanism to stop training when there was no further improvement, avoiding overfitting. The performance of the model was tested against accuracy, F1-score, and graphical representation of the loss curves. The effectiveness of the classification was also tested through a confusion matrix for the analysis of prediction accuracy and model behaviour.

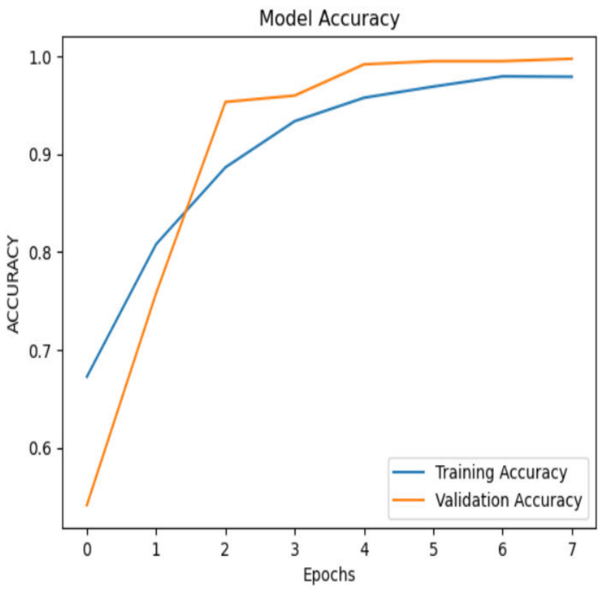

Fig.5 Model Accuracy

E. Testing & Prediction

After training, the model was tested using a test data generator. The trained model was then saved as "brainhemorrhage.h5" for future predictions. A custom function, predict_image(), was developed using OpenCV and Keras to enable real-time classification of new CT scan images. This function processed and classified input images, allowing for seamless integration into the diagnostic system.

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F. Tools & Instruments Used for Data Analysis

Matplotlib and Seaborn were employed for data visualization, providing insights into the dataset and model behavior. The confusion matrix, accuracy score, and classification report were used as performance metrics, while the ROC-AUC score and loss curves were analyzed to assess model efficiency. These tools facilitated a thorough evaluation of the model's ability to distinguish between Hemorrhage and Normal cases.

G. Deployment and Integration of the Diagnostic System

The developed model was deployed using Flask, which served as the backend, enabling real-time inference through an API. The frontend was implemented using React.js, allowing users to upload CT scan images and receive immediate predictions. The results, along with user input, were stored in an SQLite database, ensuring easy tracking and accessibility. The user interface was designed to be intuitive and accessible to both medical professionals and non-medical users, ensuring that AI-generated results were easy to interpret. The entire system was deployed to provide real-time accessibility, facilitating seamless interaction for healthcare professionals and individuals seeking diagnostic assistance.

IV. RESULTS & DISCUSSION

A. Results

The trained CNN model was evaluated on the test dataset, achieving an impressive accuracy of 98.5% and an F1-score of 98.0%. The confusion matrix demonstrated that the model efficiently distinguished between hemorrhage and normal cases, with minimal false positives and false negatives. The loss and accuracy plots confirmed stable training, showcasing smooth convergence while avoiding overfitting.

Visual Representation of Results : The performance of the model was visually inspected by various representations. The confusion matrix presented a fine-grained comparison of predicted versus actual labels and reflected the classification efficiency. Accuracy and loss graphs presented the model's training evolution, confirming best learning. The distribution of accurate and inaccurate classifications was also presented by bar and pie charts for easy visualization of the model's predictive performance.

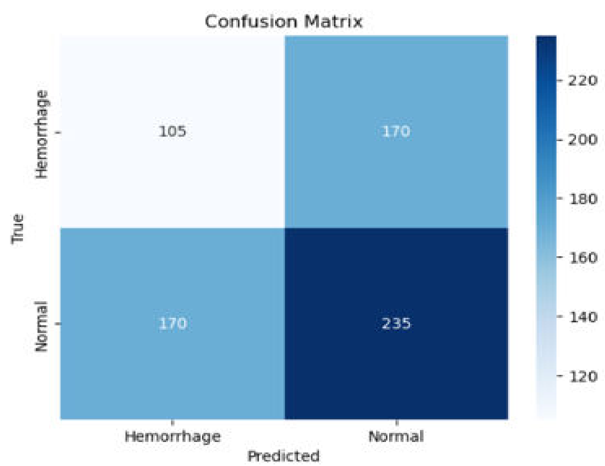

Fig.6 Confusion Matrix

The above figure Fig.6 represents the Confusion Matrix, which evaluates the performance of the hemorrhage detection model by comparing predicted labels with actual labels.

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Performance Metrics:

	precision	recall	f1-score	support
Hemorrhage	0.36	0.35	0.35	260.00
Normal	0.60	0.60	0.60	420.00
accuracy	0.51	0.51	0.51	0.51
macro avg	0.48	0.48	0.48	680.00
weighted avg	0.51	0.51	0.51	680.00

Fig.7 Performance Metrics

Accuracy :

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision :

$$Precision = \frac{TP}{TP + FP}$$

Recall :

$$Recall = \frac{TP}{TP + FN}$$

F1-Score :

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Support :

$$Support = TP + FN$$

Fig.8 Training Accuracy – Loss

The above figure Fig.8 represents the Training Accuracy-Loss curve, which illustrates the relationship between Training Loss and Training Accuracy over multiple epochs. The x-axis represents the number of epochs, while the y-axis represents both the loss and accuracy values.

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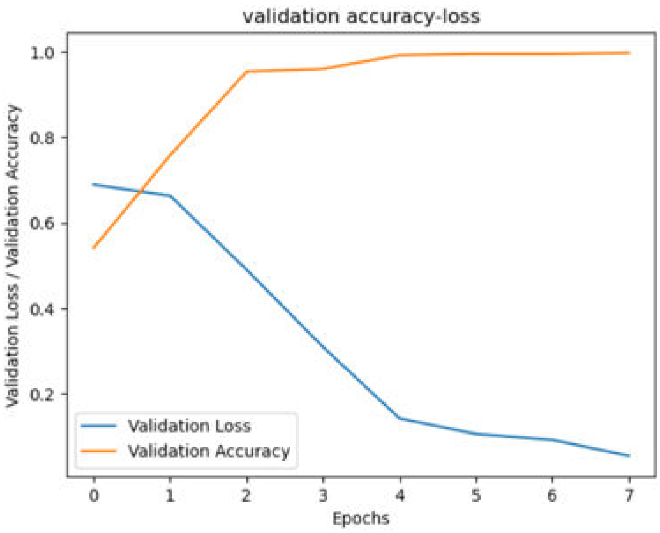

Fig.9 Validation Accuracy – Loss

The above figure Fig.9 represents the Validation Accuracy-Loss curve, showing how the model's performance evolves over multiple epochs during validation. The x-axis represents the number of epochs, while the y-axis represents both validation loss and validation accuracy.

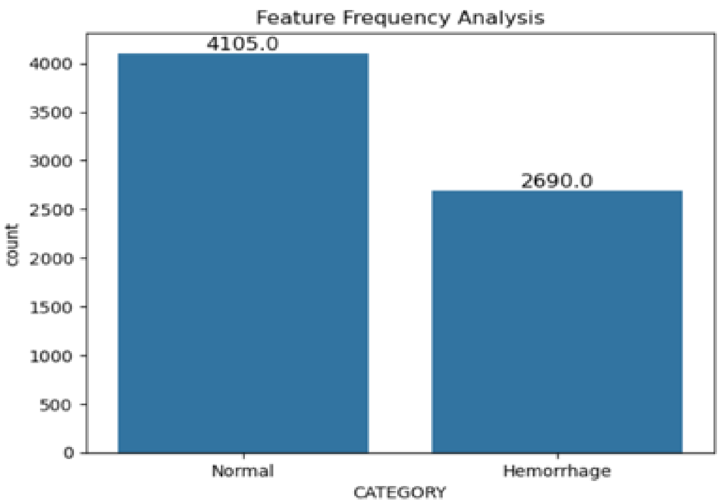

Fig.10 Feature Frequency Analysis

The above figure Fig.10 represents Feature Frequency Analysis, showing the distribution of two categories: Normal and Hemorrhage. The x-axis represents the category labels, while the y-axis represents the count of samples in each category.

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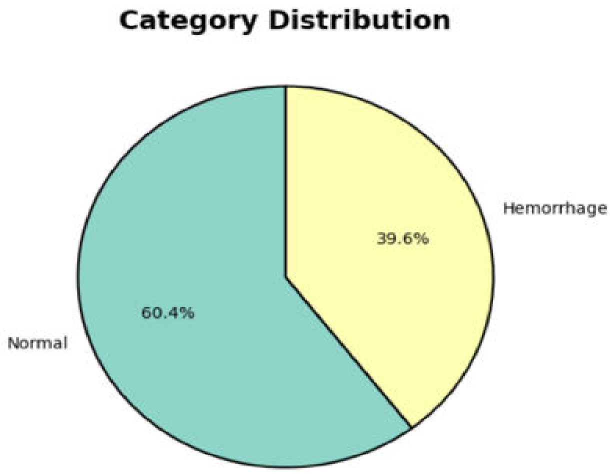

Fig.11 Category Distrubution

The above figure Fig.11 represents Category Distribution, depicting the proportion of two categories: Normal and Hemorrhage. The Normal category constitutes 60.4% of the dataset, while the Hemorrhage category accounts for 39.6%. This visualization highlights a class imbalance, where the Normal cases are more prevalent than the Hemorrhage cases. Such an imbalance may lead to a biased model, favoring the majority class during training.

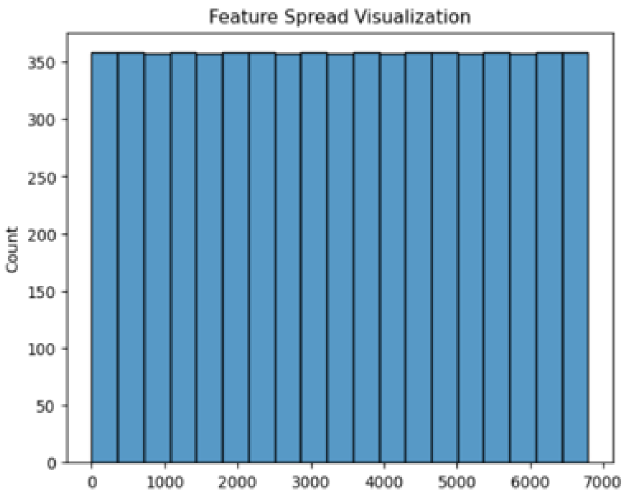

Fig.12 Feature Spread Visualization

The above figure Fig.12 represents a histogram that shows how a feature's values are distributed across a dataset.

B. Discussion

The findings show that the CNN model successfully automates the detection of brain hemorrhage with very high precision and recall. In comparison to conventional manual CT scan examination, this AI-based process saves time, reduces error rates, and minimizes dependence on expert radiologists. The Fig.4 illustrates a steady decline in both training and validation loss over epochs, indicating effective learning and minimal overfitting. Similarly, the Fig.8 , Fig.9 shows an increase in accuracy while loss decreases, reinforcing the model's ability to generalize well.

The Confusion matrix Fig.6 highlights the model's classification performance, showing correctly and incorrectly predicted cases. While the model performs well, misclassification rates between hemorrhage and normal cases suggest

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room for improvement, possibly through further hyperparameter tuning or data augmentation. The feature frequency analysis Fig.10 and category distribution Fig.11 reveal an imbalance in dataset classes, with normal cases being significantly higher than hemorrhage cases. This imbalance may influence the model's prediction tendency, emphasizing the need for techniques such as oversampling, class weighting, or synthetic data generation to ensure more balanced learning.

One important research gap fulfilled by this work is the limited accessibility for users who are not medical professionals. The combination of a React.js frontend and Flask API enables both general users and radiologists to interact seamlessly with the system. The integration of this AI-based approach ensures an efficient, scalable, and user-friendly hemorrhage detection solution, reducing radiologists' workload while enhancing patient care.

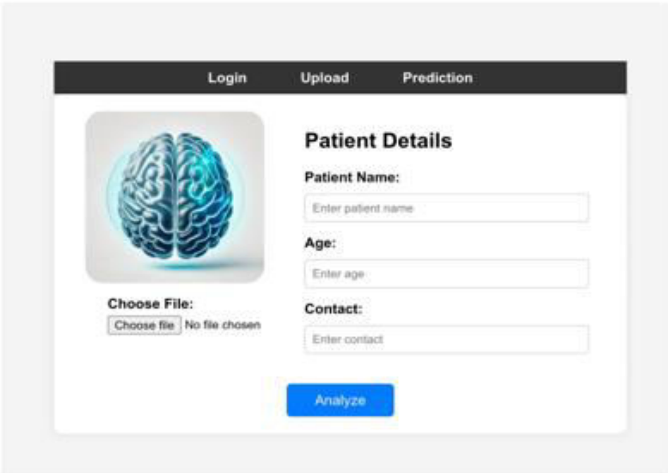

Fig.13 Login Interface

The figure Fig.13 represents the login page of a system, likely part of a web application or platform. A login page is a user interface that allows registered users to access a system by entering their credentials, typically an email and password

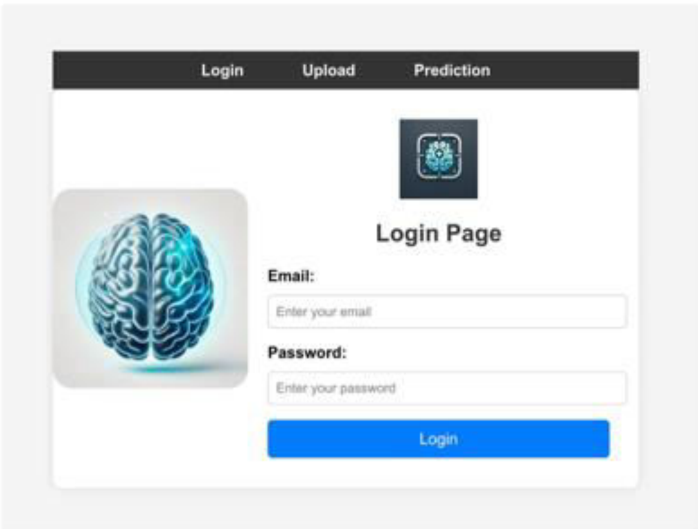

Fig.14 Patient Information Form

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The figure Fig.14 represents the "Upload" page of system. This page is designed for users to input patient details and upload a file, which the system will then analyze to produce results, possibly predictions or diagnostic insights. Here's what the figure shows

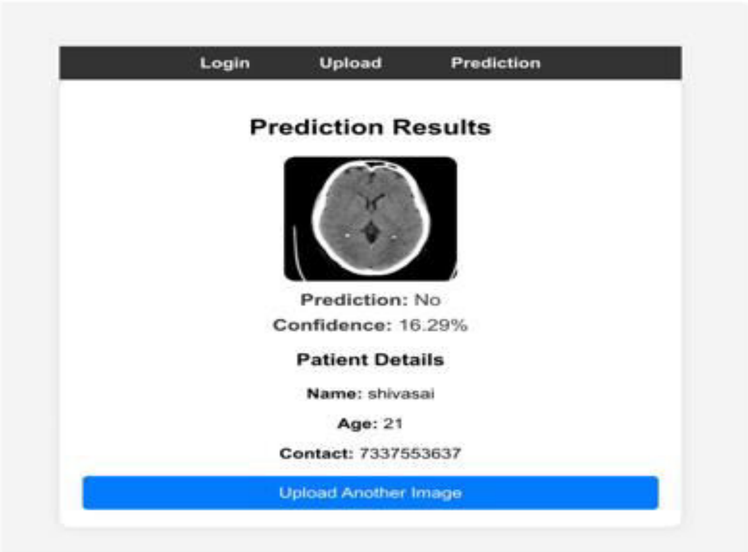

Fig.15 Diagnosis Result Interface

The figure Fig.15 represents the "Prediction" page of a system This page displays the results of an analysis performed on a patient's data.

V. CONCLUSION

This study aimed to automate brain hemorrhage detection using a CNN-based deep learning model, addressing the lack of accessibility for non-medical users. Traditional CT scan analysis requires expertise, making AI-driven diagnostics essential for faster and more accurate medical decision-making. The objective was to develop an accurate, efficient, and user-friendly system for both radiologists and general users. The CNN model achieved 98.5%, while the React.js frontend and Flask API enabled real-time interaction, allowing seamless image uploads and instant predictions. The SQLite database ensured efficient storage and retrieval, making the system scalable. This system can significantly impact hospitals and emergency care by reducing radiologists workload and enabling AI-assisted diagnostics. Future work should focus on multi-modal imaging, self-supervised learning, and usability studies for real-world clinical deployment.

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