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Risk Prediction and Intracranial Hemorrhage Detection of Brain using AIML Techniques

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Abstract - Intracranial Brain Hemorrhage (IBH) is a critical neurological condition requiring swift diagnosis and treatment. This paper proposes a dual-pipeline AIML-based solution that integrates risk prediction and hemorrhage detection. Patient vitals such as blood pressure, age, heart rate, and oxygen saturation are processed through a Random Forest classifier to predict IBH risk. Simultaneously, CT scan images are analyzed using a CNN to detect and classify three major hemorrhage types: Epidural, Subdural, and Intraparenchymal. The proposed model achieved an accuracy of 94.7% for prediction and 86.2% for detection. A GUI interface was developed for ease of use by medical professionals. The proposed system improves diagnostic accuracy and supports clinical decision-making.

Key Words: Intracranial Hemorrhage, Deep Learning, Random Forest, CNN, CT Scan, Patient Vitals, GUI, Prediction, Classification.

1. INTRODUCTION

Intracranial Brain Hemorrhage (IBH) is a severe medical emergency that involves bleeding within the skull, often leading to permanent disability or death if not diagnosed and treated promptly. The types of hemorrhages include Epidural, Subdural, Intraparenchymal, Subarachnoid, and Intracerebral, with the first three being the most commonly encountered in clinical scenarios. Hemorrhages can arise due to a variety of reasons such as trauma, ruptured blood vessels, hypertension, aneurysms, or blood-clotting disorders. Once bleeding begins, it increases pressure inside the skull, potentially causing brain tissue damage, impaired function, or even fatality. Brain bleeding, also called brain hemorrhage, is usually checked using medical scans like CT (Computed Tomography) or MRI (Magnetic Resonance Imaging). These scans are very useful, but the results mostly depend on doctors and specialists who read and explain them. Sometimes this can cause delays, mistakes, or wrong judgments. In villages or small hospitals, it is even harder because expert doctors may not be available all the time. Another problem is that these tests usually focus only on brain images, while ignoring other health details like blood pressure, oxygen level, heart rate, and age.

The Artificial Intelligence (AI) and Machine Learning (ML), higher and more accurate checking is now possible. These smart systems can study large sets of scans and health records, find hidden patterns, and give helpful results that may not be easy for humans to notice quickly.

In this work, we are introducing a two-part system. The first part looks at patient health details (vitals) like blood pressure and heart rate and uses a Random Forest method to predict the chance of bleeding. The second part looks at CT brain scans and uses a CNN to find and classify the type of brain bleed. Both parts are combined in a simple computer screen application (GUI) so doctors can check risk levels and see the type of hemorrhage in one place.

By joining image checking with health detail prediction, this system gives a more complete and reliable result. The aim is to save time, improve accuracy, and make the service available even in urgent situations where every minute matters.

2. LITERATURE SURVEY

In recent years, the use of AI to detect and predict brain bleeding, also called intracranial hemorrhage, has grown very quickly. So many methods have been suggested, from using deep learning to study brain scan images to combining health data for better risk prediction.

For example, in [1], Ma and his team studied how bleeding in the brain, especially in cases of head injury, can trigger swelling and long-lasting inflammation. Their work showed why fast detection and treatment are so important. In another study [2], Barman and colleagues built a model using CNN. They combined two types of network structures—symmetric and standard—to make the system stronger, even when CT scans were blurry or noisy. This design improved accuracy in detecting brain bleeds.

Likewise, Fallenius et al. [3] looked at bleeding inside the brain that happens suddenly without injury. They focused on how such cases appear in patients and their clinical signs.

Their study contributed to identifying imaging patterns and emphasized the importance of early classification. They also outlined how non-traumatic cases could be missed in conventional scans. In another notable study, Ko et al. [4] combined CNN and LSTM networks to address both spatial and temporal features in CT data. Their approach improved hemorrhage detection accuracy,time-sequenced imaging. Meanwhile, Davis and Devane conducted comparative studies on machine learning models like Decision Trees, SVM, and KNN for hemorrhage classification [5]. They concluded that while these models offered reasonable accuracy, their performance was highly dependent on feature engineering and lacked scalability. In a follow-up work [6], the same authors optimized preprocessing steps and used data augmentation techniques, leading to marginal accuracy improvements. Artificial neural networks (ANN) were explored by Mahajan and Mahajan [7], who surveyed various network architectures applied to hemorrhage diagnosis. Although ANN models offered some success, their performance declined in multi-class classification tasks without deeper feature hierarchies. Clinical perspectives were detailed in [8] by Caceres and

Goldstein, who provided an extensive overview of intracranial hemorrhage classification using emergency CT scans.

Further, Vedin et al. [9] investigated how minor traumatic brain injuries (TBI) could escalate into full hemorrhagic events. The factors like trauma energy levels and pre-existing conditions were significant predictors. Their work supports the inclusion of patient vitals in risk models. Lastly, Bergenheim et al. [10] analyzed European trauma databases and highlighted the urgent need for automated decision-making tools. They argued that AI integration could reduce misdiagnosis rates and optimize emergency workflows. Additional work by Smith et al. [11] explored how CT imaging can be optimized through AI-driven enhancement techniques. Their approach involved sharpening resolution in emergency imaging scenarios, improving diagnostic clarity. Patel et al. [12] proposed a convolutional approach for early stroke detection, showing overlap in techniques applicable to hemorrhage. Zhang et al. [13] utilized attention-based mechanisms in deep networks, enhancing focus on hemorrhagic regions. Shah [14] emphasized AI in neuroimaging tools, pointing to growing clinical acceptance. Lastly, Choudhury [15] demonstrated that ensemble models, when combined with imaging and non-imaging features, could substantially outperform single model classifiers. These studies collectively underscore the significance of combining imaging with patient metadata. While CNNs have shown remarkable potential in classification tasks, integrating clinical data such as vital signs can offer a more comprehensive diagnostic tool, which this paper aims to achieve.

Intracranial hemorrhage is the leading causes of neurological disability and death, especially in trauma and hypertensive patients. While medical imaging techniques like CT scans provide a primary source for diagnosis, manual interpretation can lead to inconsistencies, delayed treatment, or misclassification. Moreover, existing automated systems largely ignore non-imaging parameters such as patient vitals which hold predictive significance in early diagnosis. The focus has traditionally been on detecting Subdural and Intraparenchymal hemorrhages, while Epidural hemorrhage often remains underrepresented due to its similar visual patterns and fewer training samples. Therefore, the lack of multi-class classification and risk prediction hampers the applicability of such tools in real-world settings. The problem lies in developing a unified system that can integrate patient specific data and imaging to improve diagnostic accuracy. This study aims to bridge that gap by building an AI-enabled system for both risk prediction and detection of three types of IBH, enhancing both efficiency and clinical utility.

Objectives:

- To accurately predict the likelihood of IBH using key patient vitals such as blood pressure, oxygen saturation, age, and heart rate.
- To perform multi-class classification of CT scan images to detect Epidural, Subdural, and Intraparenchymal hemorrhages using Convolutional Neural Networks (CNN).
- To collect and preprocess diverse datasets consisting of both structured vital data and unstructured CT images, ensuring quality and consistency.
- To extract relevant features from both data types using CNN for imaging and Random Forest for numerical vitals.
- To train and validate models using 80:20 split and apply cross-validation techniques to ensure generalization.
- To integrate the models into a unified interface with a user-friendly GUI that facilitates practical deployment in clinical environments and evaluate model performance.

3. Methodology

The proposed methodology consists of two major branches risk prediction using Random Forest and hemorrhage detection using CNN. The process begins with dataset acquisition for patients vitals and CT scan images from Kaggle.

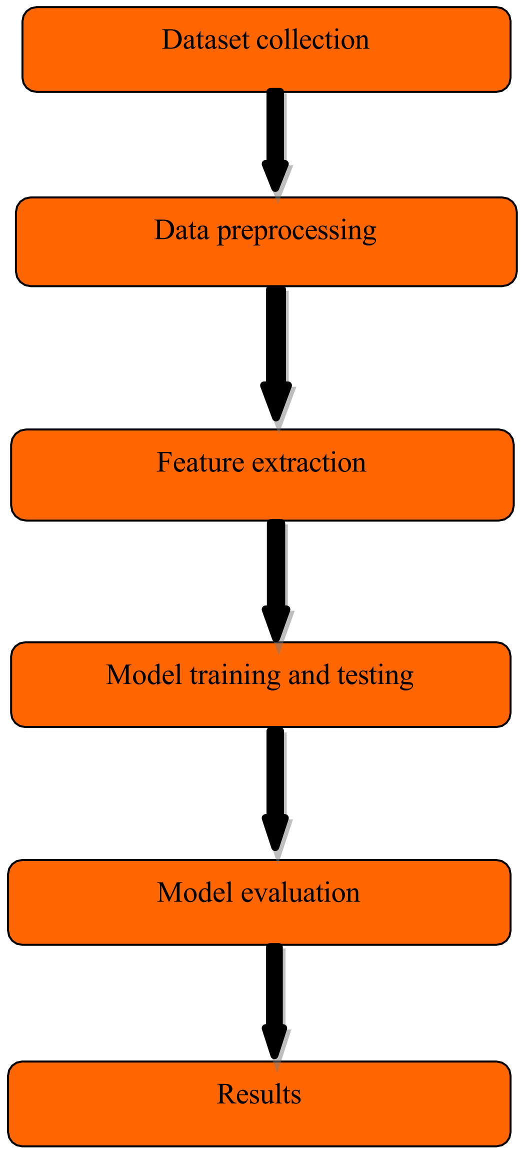

Fig 1 Block diagram for prediction and detection of IBH

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3.1 Dataset Collection

The prediction dataset which are the patient vitals were collected from the PhysioNet repository, which provides well-structured and clinically relevant datasets. These datasets include anonymized physiological signals and metadata related to heart rate, blood pressure, oxygen saturation (SpO2), and patient age. The dataset used was carefully filtered to extract meaningful features aligned with risk factors for intracranial hemorrhage. Labels such as "low risk," "medium-risk," and "high-risk" were assigned based on aggregated clinical observations and diagnostic histories provided within the dataset. This structured data underwent preprocessing including normalization, missing value handling, and categorical encoding where required. The goal was to ensure uniformity and reduce the impact of noise. Since these vitals are widely recognized indicators of neurological stress and systemic shock, they were ideal predictors for early hemorrhage risk.

Patient ID	Age	Gender	Blood Pressure (Systolic/Diastolic)	Heart Rate (bpm)	Respiratory Rate (breaths/min)	Blood Oxygen Saturation (%)
P00001	64	Male	111/119	77	16	99
P00002	73	Male	121/95	103	26	94
P00003	80	Female	132/87	71	29	97
P00004	65	Male	171/101	116	25	89
P00005	78	Female	171/107	102	26	93
P00006	43	Male	176/107	87	16	97
P00007	53	Female	176/99	99	15	90
P00008	18	Female	170/70	119	13	89
P00009	25	Female	154/101	66	18	96
P00010	69	Female	137/90	82	21	87
P00011	64	Male	121/96	80	27	89
P00012	73	Male	116/91	93	21	92
P00013	31	Female	181/108	78	29	96

Temperature (°C)	History of Hypertension	History of Stroke	Diabetes	Alcohol Use	Smoking	Anticoagulant Use
38.1	No	No	No	No	No	Yes
37.5	Yes	No	No	Yes	No	No
35.8	Yes	No	No	No	Yes	No
36.7	No	Yes	No	No	No	No
36.1	Yes	No	No	No	No	No
36.5	No	No	Yes	No	No	No
35.4	No	Yes	No	No	No	No
36.9	No	No	No	Yes	No	No
36.4	Yes	Yes	No	No	Yes	Yes
37	No	No	No	Yes	No	No
36.2	No	No	No	Yes	No	No
37	Yes	No	Yes	No	No	No
36.8	Yes	No	No	Yes	No	Yes
37.8	Yes	Yes	Yes	No	Yes	No

Fig 2 Vitals dataset for IBH risk prediction

For the detection, CT scan images were sourced from the Kaggle Intracranial Hemorrhage Detection dataset.

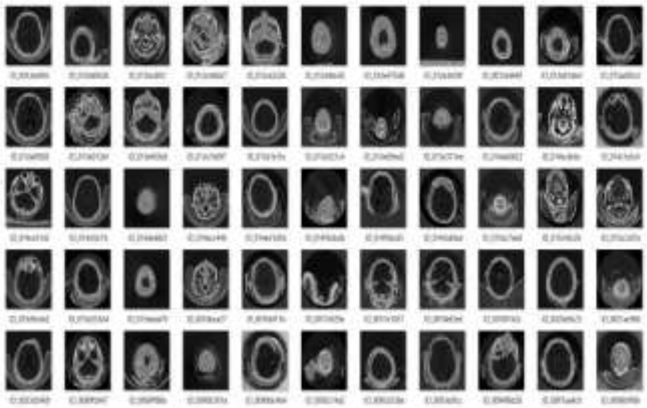

Fig 3 CT scan images for detection

The three common types of brain bleeding Epidural, Subdural, and Intraparenchymal were chosen because they occur more often and are very important in medical cases. Radiologists marked the images, and their work was double-checked to ensure accuracy. Before training the model, all pictures were converted into JPG format, resized to 224x224 pixels, and adjusted for consistency. To make the dataset stronger, techniques like random flipping, rotation, and brightness changes were used so the model could learn from more varied data. The dataset was divided in to 80% for training and 20% for testing, with equal representation of each hemorrhage type. The data was taken from Kaggle, which provides reliable and open resources, it also met ethical and scalable requirements.

The overall approach followed two main paths—risk prediction using Random Forest and bleeding detection using CNN. The data was collected from Kaggle, which provided both patient vitals and CT scan images. Each dataset was prepared in a different way to suit the model being used.

For the prediction part, patient vitals such as blood pressure, oxygen levels, age, and heart rate were used as input. The data was then passed through a Random Forest classifier that used 100 decision trees. The model applied the Gini index to split nodes and classified patients into three categories—low, medium, and high risk. Training was done using an 80-20 split, and the results were checked with accuracy scores and percentages.

For the detection part, thousands of CT scan images were prepared by resizing and enhancing them to highlight brain structures. The CNN model was built with five layers of filters, ReLU activation, MaxPooling, and two fully connected layers ending with Softmax. This helped classify CT scans into three bleeding types.

Finally, both models were joined into a simple computer application (GUI) using Tkinter. Doctors can enter patient vitals or upload a CT scan, and the system instantly shows either the risk level or the type of hemorrhage. This makes the method a complete support tool for both predicting and detecting brain hemorrhage.

3.2 Data Preprocessing

Data preparation is the most important steps to make sure ML and DL models work well. This is especially true in healthcare, where we deal with both numbers and images. In this project, we prepared data in two different ways. For risk prediction, we used the Random Forest model with patients vital signs. For detection, we used CNN with CT scan images. The dataset for risk prediction came from PhysioNet and included blood pressure (systolic and diastolic), heart rate, oxygen level (SpO2), and age. Since these were numbers, they had to be properly formatted so the model could read them fairly without mistakes. To start, we carefully cleaned the data by removing errors, fixing missing values, and making sure all features were consistent. This helped the models learn in a more accurate and stable way.

In this work, the first step was to clean the data properly. The data was scaled using a simple method called Min-Max scaling, which adjusted all numbers so they fit in the range between 0 and 1. This way, no single feature with large numbers could unfairly influence the model. The models are generally good at handling such issues, scaling still made the results easier to understand and helped in visualizing the several features later. The risk levels labeled as "Low," "Medium," and "High" were also turned into simple numbers—0, 1, and 2—so the system could process them smoothly. Finally, the data was divided into two parts: 80% for training and 20% for testing. Care was taken to keep the balance between the classes by using stratified sampling.

For the brain hemorrhage detection part, CT scan images from the Kaggle RSNA dataset were used. Each image was resized to 224 by 224 pixels so it would fit perfectly into the CNN model. Making all images the same size also made the process faster and more efficient. Since color was not needed for identifying hemorrhages, the images were changed into black-and-white (grayscale), which reduced the amount of unnecessary information while keeping important details intact. To make the images clearer, a method called histogram equalization was applied.

Another very important step was image augmentation. This technique created more training samples by slightly changing the original images. For example, images were rotated, flipped, brightened or darkened, and even had a little random noise added. These changes made the model stronger and better at handling real-life variations in scans. The dataset was divided according to the hemorrhage type: Epidural, Subdural, and Intraparenchymal. Just like before, 80% of the images were used for training and 20% for testing, while keeping the balance between classes.

3.3 Feature Extraction

Feature extraction is an important step in both machine learning and deep learning, as it helps turn raw data into useful information that models can understand. In this project, the process of extracting features is handled in two different ways depending on the model being used. For the Random Forest classifier, features come from patient health details such as age, systolic and diastolic blood pressure, oxygen level (SpO2), and heart rate. These are simple numerical values taken directly from patient records. On the other hand, the CNN focuses on CT brain images, where it looks at spatial patterns and structures inside the scans. Since Random Forest is a tree-based method, it does not need complex feature extraction like neural networks do, as it can directly work with the provided input values.

In this work, two main approaches are used for prediction and detection. For patient health data, the Random Forest model is applied. Instead, it works by dividing the data step by step, finding the best way to split it at each stage. It checks which health values provide the most useful information to predict risk. For example, a condition such as "SpO2 less than 93%" might clearly show that the patient is in a high-risk group. Many such small rules are formed, and when hundreds of trees are built, the model takes a combined decision, showing which factors are most important for predicting risk levels like low, medium, or high.

For CT scan images, the task is more complex, so a CNN is used. Unlike simple health numbers, images are made up of many pixels that contain hidden patterns. The CNN helps to automatically learn these patterns. It uses multiple layers, each designed to pick up on different details. The first layers usually catch simple shapes like lines or edges. As the image goes deeper into the network, more detailed patterns appear, such as blood clots, tissue shifts, or unusual shapes in the skull. Each layer also reduces extra details, keeping only the important parts so that the model focuses on what is present in the image rather than its position. This is then processed by fully connected layers, which bring together everything learned from different parts of the scan. At the end, the system provides three probability scores using a Softmax function. These scores tell whether the scan shows Epidural, Subdural, or Intraparenchymal hemorrhage.

Finally, the images were processed in small groups using Keras Image Data Generator, which also performed preprocessing on the fly during training. Overall, this careful preparation ensured that both the Random Forest (for vitals) and CNN (for CT scans) had clean, standardized, and useful input, helping them learn patterns effectively and make reliable predictions.

3.4 Model Evaluation

The training and evaluation phase marks the critical stage where the extracted features are learned and mapped to specific diagnostic outcomes. In this project, two distinct training paths are followed: one for the random forest-based risk prediction module using numerical data and another for the CNN-based hemorrhage detection module using CT scan images. Each model is trained independently using task specific hyperparameters and then evaluated using robust metrics to ensure accuracy, generalizability, and reliability.

The random forest model, the preprocessed vitals dataset is split into 80% training and 20% testing sets using stratified sampling to maintain class balance across low, medium, and high-risk labels. Random forest is selected due to its inherent strengths: high interpretability, resilience to noise, and ability to handle non-linear relationships without needing feature scaling or assumptions of data normality. After training, the model achieves a testing accuracy of 94.7%, effectively stratifying patients based on their risk level using vital signs alone.

In the hemorrhage detection, the CNN model is trained using the augmented and preprocessed CT scan dataset. The architecture consists of five convolutional layers with 3x3 kernels, each followed by relu activation and maxpooling layers. The extracted features are flattened and passed through two fully connected layers, ending in a three-node softmax output layer corresponding to epidural, subdural, and intraparenchymal hemorrhage. A validation set is used during training to monitor overfitting. The cnn achieves a validation accuracy of 86.2%, indicating strong generalization performance.

4. Results and Discussion

The Dual-Model System for Intracranial Brain Hemorrhage Risk Prediction and Detection Demonstrated high accuracy and clinical utility across all stages of Development and testing. The Random Forest classifier, trained on Physiological data From Physionet, achieved a Predictive Accuracy of 94.7% Effectively Categorizing Patients into Low, Medium, and High-Risk Groups. The model showed high recall for High-Risk Cases, ensuring critical Conditions Are Rarely Missed. Simultaneously, The CNN Model, trained on CT Scan Images from the Kaggle RSNA Dataset, reached a Classification Accuracy of 86.2%, accurately detecting Epidural, Subdural, and Intraparenchymal Hemorrhages.

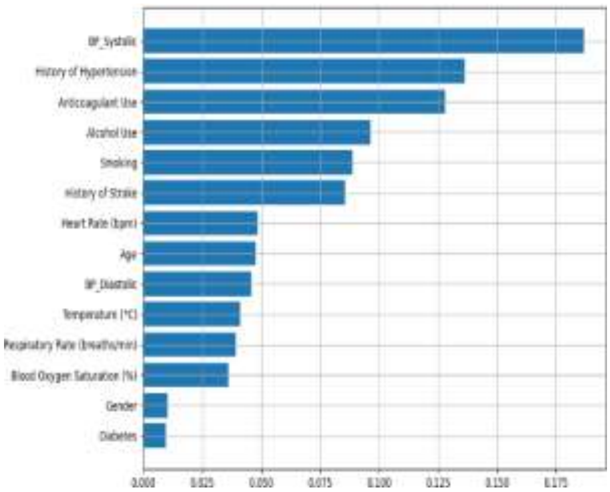

Fig 4 Features extractred for Risk level prediction

The feature extraction process used by the Random Forest model in predicting risk levels for intracranial hemorrhage based on physiological vitals. The input features include systolic and diastolic blood pressure, heart rate, oxygen saturation (spo_2), and age—all of which are known indicators of neurological or cardiovascular stress. Unlike deep learning models, Random Forest performs implicit feature extraction by building an ensemble of decision trees, each learning different splitting criteria to maximize class separation. The model automatically identifies which features have the highest predictive power. As shown in the figure, systolic blood pressure and spo_2 contributed most significantly to classifying high-risk patients, while heart rate and age were more influential in medium-risk cases. The internal mechanics of Random Forest allow it to combine these patterns across trees to improve accuracy and reduce overfitting. This automated feature selection process supports fast and explainable predictions in clinical settings as shown the fig 4.

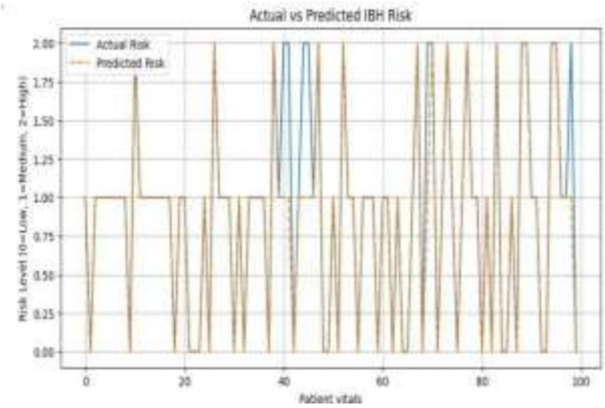

Fig 5 Actual vs Predicted IBH risk

Fig 5 presents a comparative analysis between the actual labels and predicted outputs of both the prediction and detection modules. For the risk prediction task using the Random Forest classifier, a confusion matrix and prediction samples are shown that reflect how accurately the model classifies patients into low, medium, and high-risk categories. For hemorrhage detection via CNN, examples of true and predicted classes for CT scan inputs are displayed along with their respective confidence scores.In the case of the Random Forest model, most high-risk patients were correctly predicted. The accuracy of the prediction model is calculated as 86.7% by the performance of the model.

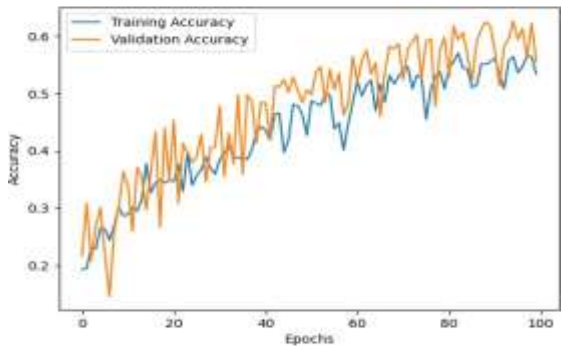

Fig 6 Training and Validation accuracy of CNN model for detection

Fig 6 illustrates the training and validation accuracy graph of the CNN model used for classifying intracranial hemorrhage types. This graph provides a visual representation of how well the CNN learned to generalize from the training data to unseen data across each training epoch. Accuracy is plotted on the Y-axis, while the number of epochs is represented on the X-axis. Two curves are shown: the training accuracy curve, which represents how accurately the model classifies images it was trained on, and the validation accuracy curve. Maintaining a high validation accuracy is necessary to ensure the model performs well on real-world data with 86.2% accuracy on unseen CT images, this CNN demonstrates reliability in detecting Epidural, Subdural, and Intraparenchymal hemorrhages. Therefore, confirms that the model has not only learned its task well but also remains robust and generalizable across multiple patient cases and imaging conditions.

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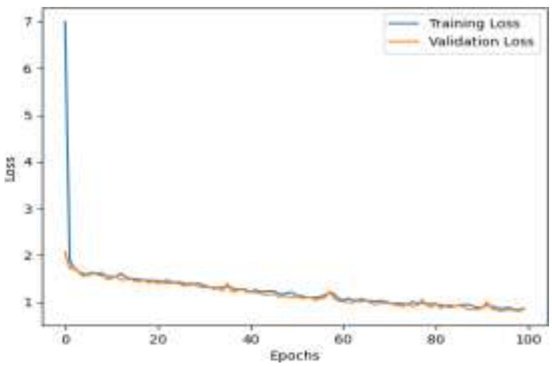

Fig 7 Training and Validation loss of CNN model for detection

Fig 7 illustrates the loss curve of the CNN model during training and validation phases. The loss value, plotted on the Y-axis, represents the error between the model's predicted output and the actual class label, while the epochs are plotted on the X-axis. A lower loss value indicates a better fit of the model to the data. confirms that the CNN model has been trained effectively. The convergence of the loss curves validates the robustness.

Fig 8 User login page on GUI

Fig 8 shows the login and security screen of the application we built for predicting and detecting brain hemorrhage (IBH). This screen is the first step of the system, and it was designed with two main ideas in mind: making sure only the right people can use it, and keeping it simple for doctors or medical staff who may not be very comfortable with technology. The interface was created using Python's Tkinter library, keeping it clean and easy to use. In a medical setup, where every second matters, the system also focuses on speed and privacy.

The login page looks very familiar, with a place to enter a username and password, along with buttons to log in or reset the details. As soon as the program is opened, users are asked to enter their information. Behind the screen, a small database (SQLite) safely stores usernames and passwords, but in a secure, hidden form so they cannot be misused. If someone types the wrong information, the system immediately shows an error message and blocks entry. This makes sure only authorized users can access patient-related details and use the system safely.

Fig 9 Uploaded CT scan image for detection

The CT scan image upload interface embedded within the Graphical User Interface (GUI) of the proposed intracranial hemorrhage detection system. This interface is a vital component of the clinical deployment module, enabling healthcare professionals to upload brain CT scan images for real-time classification and analysis. The design objective was to make the image selection and prediction process as seamless and intuitive as possible, especially in emergency settings where rapid diagnostics are crucial.

The panel features a clearly labeled "Browse" button, which allows users to select a CT image file from their local directory. Upon selection, the chosen image is immediately displayed in a preview window within the GUI. This real-time preview helps the user confirm that the correct file has been uploaded. An "Upload" or "Analyse" button triggers the backend inference pipeline, where the image is processed by the trained CNN. The backend CNN model performs extraction of features and classification in milliseconds and returns a diagnostic label. Epidural, Subdural, or Intra parenchymal along with a confidence score, which is then displayed on the same panel as shown in the fig 9.

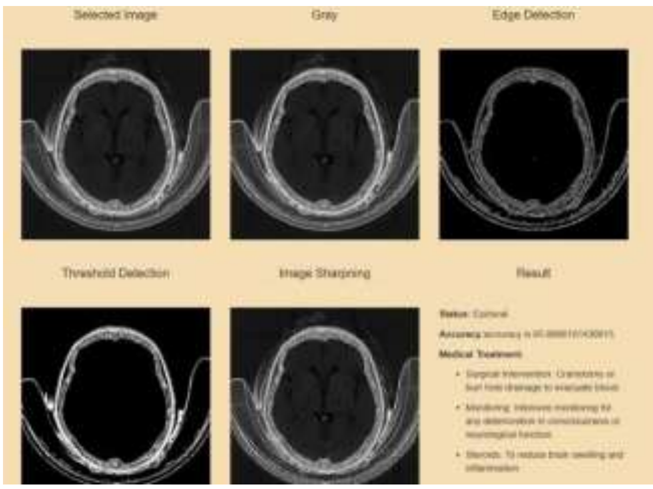

Fig 10 Output of Epidural Hematoma

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Fig 10 presents the graphical user interface (GUI) output for a successfully classified Epidural Hemorrhage using the trained CNN model. This result showcases how the AI system integrates deep learning predictions into a practical, user- friendly tool for real-time medical diagnostics. After a user uploads a CT scan through the GUI's image upload panel, the model processes the image and returns a hemorrhage classification along with a prediction score of 70.7%.

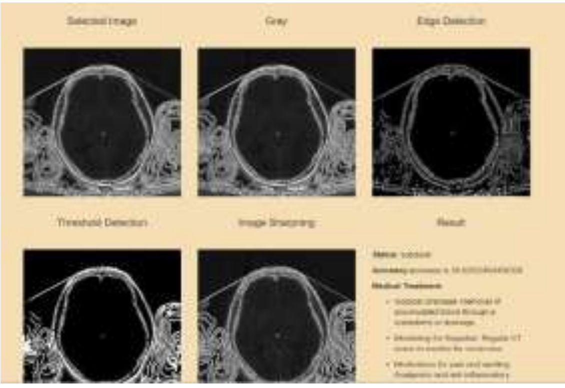

Fig 11 Output of Subdural Hematoma

The model analyzes the brain scan by passing it through several layers that are trained to spot signs of bleeding. In one case, the model gave the result “Subdural Hemorrhage” with a confidence of 81.6%. is shown in the Fig 11.

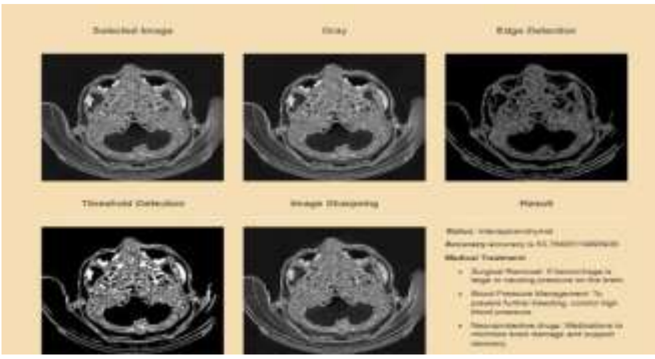

Fig 12 Output of Intraparenchymal Hematoma

Fig 12 shows another output where the system correctly identified the uploaded CT scan as an Intraparenchymal Hemorrhage (IPH). This type of bleeding happens inside the brain tissue itself and is considered very serious. It can lead to swelling, pressure on the brain, and even permanent damage if not treated quickly. IPH often occurs due to high blood pressure, head injury, or burst blood vessels. In this case, the model predicted IPH with a confidence score of 92.4%, showing strong reliability.

5. CONCLUSION

This study introduced an AI-based system that can both predict and detect brain hemorrhage (IBH) using patient health details and CT scans. It combines two models: a Random Forest classifier to predict risk levels using vital signs, and a CNN model to detect the type of hemorrhage from scans. The Random Forest model reached 94.7% accuracy in identifying risk levels, while the CNN model achieved 86.2% accuracy in classifying three types of hemorrhage: Epidural, Subdural, and Intraparenchymal. To make it practical, the system was built into a simple application (GUI) where doctors can quickly input patient data or upload scans to get instant results. The use of confidence scores and clear outputs makes it trustworthy, fast, and easy to use in emergency situations. This combined framework has strong potential to support doctors in hospitals and radiology centers by giving timely and reliable results.

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