Deep Learning Fusion for Intracranial Hemorrhage Classification in Brain CT Imaging

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***Abstract*—Brain hemorrhages are characterized by the rupture in the arteries of brain due blood clotting or high blood pressure (BP), presents a significant risk of traumatic injury or even death. This bleeding results in the damage in brain cells, with common causes including brain tumors, aneurysm, blood vessel abnormalities, amyloid angiopathy, trauma, high BP, and bleeding disorders. When a hemorrhage happens, oxygen can no longer reach the brain tissues and brain cells begin to die if they are depleted of oxygen and nutrients for longer than three or four minutes. The affected nerve cells and the related functions they control are damaged as well. Early detection of brain hemorrhages is crucial. In this paper an efficient hybrid deep learning (DL) model is proposed for the intracranial hemorrhage detection (ICH) from brain CT images. The proposed method integrates DenseNet 121 and Long Short-Term Memory (LSTM) models for the accurate classification of ICH. The DenseNet 121 model act as the feature extraction model. The experimental results demonstrated that the model attained 97.50% accuracy, 97.00% precision, 95.99% recall and 96.33% F1 score, demonstrating its effectiveness in accurately identifying and classifying ICH.**

Keywords*—*Intracranial hemorrhage; deep learning; DenseNet 121; LSTM; brain CT images

I. Introduction

Hemorrhage describes the occurrence of bleeding either internally or externally from the body. A sudden blood clot in arteries can cause brain hemorrhage, which can lead to symptoms such as tingling, palsy, weakness, and numbness. Recognizing these symptoms is crucial for initiating immediate treatment. Brain hemorrhages occur when a blood vessel in the brain leaks or bursts, results in hemorrhagic stroke. ICH is a life-threatening neurological condition that can occur due to various causes, such as increased BP, hemorrhage secondary to infarct, trauma, tumor hemorrhage, and more [1]. One of the most common causes of ICH is traumatic brain injury. When blood pools within the brain parenchyma, it forms a hematoma, which increases pressure on the surrounding brain tissues. This pressure leads to reduced blood flow and ultimately kills brain cells.

There are various forms of hemorrhages, each occurring in different areas of the skull. Epidural hemorrhage (EPD) occurs when there is damage to both the skull and the dura mater, leading to bleeding. An accumulation of blood within the brain's tissues causes an intraparenchymal hemorrhage (ITP), also, the bleeding in the brain's ventricular system is known as intraventricular hemorrhage (ITV). Subdural hemorrhage refers to a collection of blood within the subdural spaces, which are potential spaces between the dura and arachnoid of the meninges surrounding the brain. Subarachnoid hemorrhage is an extra-axial intracranial hemorrhage located within the subarachnoid spaces [2].

Diagnosing a brain hemorrhage is challenging because some individuals do not exhibit any physical signs. Computed tomography (CT) is the prime method used for the diagnosis of ICH. During a CT scan, a set of images is generated using X-ray beams, capturing the various intensities of brain cells from their X-ray absorbency levels [3]. The regions of ICH are depicted as hyperdense areas without a defined architecture. Radiologists analyze these scanned images and confirm the presence, type and location of ICH. However, the accuracy of the diagnosis depends on the accessibility and experience of the radiologist, which can lead to ineffective and impressive results [4].

In recent years, artificial intelligence (AI), particularly DL, has significantly transformed image analysis, becoming an essential tool in medical diagnostics. This study employs a new hybrid DL approach to detect and classify ICH from brain CT images. This approach combines the strengths of Advanced Neural Network (ANN) such as DenseNet 121 and LSTM to increase the accuracy and reliability of hemorrhage detection. The performances of the model are assessed using the metrics of precision, accuracy, recall, and F1 score, demonstrating its effectiveness in identifying brain hemorrhages. The proposed work offers some key contributions as follows.

- To develop a hybrid DL-based computer aided diagnosis system for early detection and classification of brain hemorrhage using brain CT images.
- To reduce the error rate of brain hemorrhage detection system.
- To train the Neural Network using more images to avoid over fitting problem.
- To improve the performance evaluation parameters precision, accuracy, F1 score and recall of the system.
- To develop a new model based on deep learning for effective segmentation from brain CT images.

The next sections of the study as follows: The current approaches are discussed in Section II. The methodology proposed is illustrated in Section III. The results are presented in Section IV. Section V concludes the paper.

II. LITERATURE REVIEW

The efficiency of a DL model for the identification of ICH and its subtypes on non-contrast CT scans was evaluated by Yeo et al. (2023) [5]. The algorithm was tested and trained on an open-source retrospective data. The training dataset was obtained from four different countries and test data were obtained from India. The performance of the convolutional neural network (CNN) was compared to that of other models that were similar. The performances of the model were evaluated using the area under curve characteristics (AUC-ROC) and micro-averaged precision (mAP) score. The performance of mAP increased from 0.77 to 0.93, and AUC-ROC increased from 0.854 to 0.966. The study highlighted its limitations, that the performance of the model was not tested on images that were subjected to different CT image reconstruction methods. Additionally, the datasets used in the study contained class imbalances.

Rajagopal et al. (2023) [6] provided an ICH classification with six separate types of hemorrhages in circumstances where patients experienced several hemorrhages continuously. The different types of ICH present were detected and classified using the CT scan of patient's skull. This study presents a hybrid approach combining CNN and LSTM for enhanced performance. The RSNA dataset was utilized to assess the model's performance. The model achieved 93.87% sensitivity, 96.45% specificity, 95.21% precision and 95.14% accuracy.

Luis et al. (2023) [7] proposed an Efficient DL method for the diagnosis of hemorrhages in patients. The technique classified the slices of CT scans for hemorrhage. The model was evaluated to check whether the patient was positive and achieved 0.978 ROC AUC and 92.7% accuracy. The study proves that the framework can be used as an assistant for CT-based diagnosis.

Tharek et al. (2022) [8] created an algorithm for identifying ICH in head CT scan. This algorithm module was developed by CNN using deep learning. In this study 200 data were collected from a public dataset. The algorithm was trained using Jupyter Notebook platform. A confusion matrix was used to evaluate the model's performance which results in 96.94% sensitivity, 93.14% specificity, 93.14% precision and 95.00% of accuracy with 95% F1 score. The study proves that DL using CNN created an accurate classifier.

An AI-based method for ICH on non-contrast CT images was presented by Seyam et al. (2022) [9]. The entire ICH detection attained 93% diagnostic accuracy, 97.8% negative predictive value and 87.2% sensitivity. The study highlighted its limitation such as, the proposed work did not contain complete metrics data for all patients.

Ganeshkumar et al. (2022) [10] proposed an unsupervised DL framework for CT image-based ICH identification. Principal Component Analysis (PCA-Net) was utilized by the model to extract features from CT scans. The models were tested and trained using 752 and 1750 CT slices. The proposed framework achieved 67% accuracy, 80% weighted average precision and 67% weighted average recall additionally with an F1 score of 72% indicates that the method act as an unsupervised framework for identifying ICH from CT images.

Ganeshkumar et al. (2022) [11] studied the segmentation and identification of ICH regions in CT images and proposed a one-stop model. The framework used ResNet for identification and an adversarial network SegAN for segmentation. Therefore, the approach achieved an F1 score of 0.91 on a macro average, 0.80 on sensitivity, and 0.99 on specificity for ICH identification. Additionally, the model received a dice score of 0.32 for the ICH segmentation. Thus, the segmentation and identification method helped doctors in making accurate diagnoses. The study noted limitations, such as the method not being capable of classifying the identified ICH and the dataset used being of small size.

A DL-based ICH diagnosis model called GC-SDL was created by Anupama et al. (2022) [12] utilizing GrabCut-based segmentation with synergic deep learning (SDL). The framework used a Gabor filter for removing the noise. The segmentation method was applied to identify the portions affected. The feature extraction process was performed using SDL and softmax was applied as a classifier. The results showed that the model achieved 97.78% specificity, 95.73% accuracy, 94.01% sensitivity, and 95.79% precision.

Wu et al. (2021) [13] introduced an ensemble deep neural network (DNN) for the identification and categorization of ICH in their study. There are two parallel network pathways in the method. Both pathways used the EfficientNet-B0 as their core architecture, which was then assembled to produce predictions. The models were trained and evaluated using the ICH detection dataset comprising of 674,259 head noncontract CT images from 19,531 patients. In addition, the generalizability of the trained model was tested using another dataset, CQ500. The performance of ICH detection dataset resulted in 95.7% accuracy, 85.9% sensitivity and 86.7% F1 score. Similarly, it resulted in 92.4% accuracy, 93.4% F1 score and 92.6% sensitivity when utilizing the CQ500 dataset. A limitation of the study highlighted that the performance of the framework was not compared with the radiologist diagnostic performance.

In order to accomplish accurate ICH identification, Wang et al. (2021) [14] developed a DL technique that replicates the radiologist's interpretation process by merging a 2D CNN model with a two-sequence model. The 2019-RSNA Brain CT Hemorrhage Challenge dataset, which included over 25,000 CT images that correctly identified ICH, was used to create the technique. Using 491 and 75 CT images, respectively, the system was tested on two separate external validation sets, maintaining 0.949 AUC and 0.964 ICH detection. The results demonstrate the suggested model's excellent performance and capacity for generalization. The study found that the model's training required greater time and complexity.

To save the time needed to identify hemorrhages, Rohit (2021) [15] looked at the ICH detection problem in his study and created a DL model and a transfer learning (TL) model. To ensure the accuracy of the model, DenseNet 121, CNN, and Xception were compared using a variety of evaluation criteria. The accuracy of 91% was achieved in the ICH detection and classification using the suggested CNN and TL models. The Xception model was capable of identifying the ICH with lower risk of failure.

Using Inception Network for effective image segmentation, Mansour and Aljehane (2021) [16] created a DL-based ICH model (DL-ICH). The model proposed involves several processing steps. A multilayer perceptron (MLP) was utilized for classification, while an inception v4 network was employed for feature extraction. The model's output is compared with a series of simulations showed that its accuracy, precision, and sensitivity were 95.06%, 97.56%, 95.25%, and 93.56%, respectively.

In their study Bhadauria et al. (2021) [17] presented a segmentation method for the extraction of hemorrhage from brain CT images using fuzzy clustering features. Fuzzy clustering was utilized to estimate the parameters that controls the propagation of the level set function. The model utilized a dataset consisting of 300 CT images with various shapes of hemorrhages and sizes. The performance of the proposed model resulted in 85.40% accuracy, 98.79% specificity and 79.91% sensitivity. The study noted a limitation in that using a denoising algorithm on the system, resulted in increased complexity and longer processing times.

A densely connected CNN (DenseNet) with extreme machine learning (EML) was developed by Santhoshkumar et al. (2021) [18] for the purpose of diagnosing and classifying ICH. The model uses DenseNet for feature extraction and Tsallis entropy in conjunction with a grasshopper optimization approach for image segmentation. The results of the simulation verified that the model has reached its highest accuracy level of 96.34%.

Lee et al. (2020) [19] in their study introduced a DL algorithm for artificial neural network (ANN). This study evaluated the feasibility of using the algorithm for detecting and classifying ICH without employing CNNs. The model achieved 0.859 AUC, 78% sensitivity and 80% specificity for the detection of ICH. For the localization of ICH, the CT images attained 0.903 AUC, 82.5% sensitivity and 84.1% specificity. The accuracy rate is 91.7% for the classification of ICH. The study reduced the ICH diagnosis time. The limitation suggest that the size of the dataset used was small.

There are several notable gaps in the current methods for analyzing brain CT images. The magnification factor affects brain CT images, leading to misclassification and reduced performance. Image segmentation cannot be used in certain works, showing the difficulty in determining the correct location of internal bleedings from CT scans. Another disadvantage is the dependence on a manual reference provided by a single human expert. Hemorrhages and microaneurysms have same characteristics and are only distinguishable by their color and size on color fundus images, making them easily misunderstood. False positive rates are high for classification and segmentation. Lastly, existing classification methods suffer from lower accuracy and sensitivity indicating a clear need for improvement in these areas.

III. Materials and Methods

The block diagram depicted in Fig. 1, illustrates the process of ICH classification using a hybrid deep learning approach from brain CT images. The model takes CT images from the dataset as input. The images undergo data preprocessing and augmentation. The DenseNet 121 model uses the preprocessed images as input to extract features. The extracted features are reshaped into sequential patterns and given as an input to the LSTM. The model grasps the temporal connections and sequential dependencies within the data. The LSTM output is directed to a dense layer to group the learned features followed by a softmax layer for final classification. The classification outputs determine whether the CT image indicates a normal or hemorrhagic condition, thus ensuring accurate diagnosis.

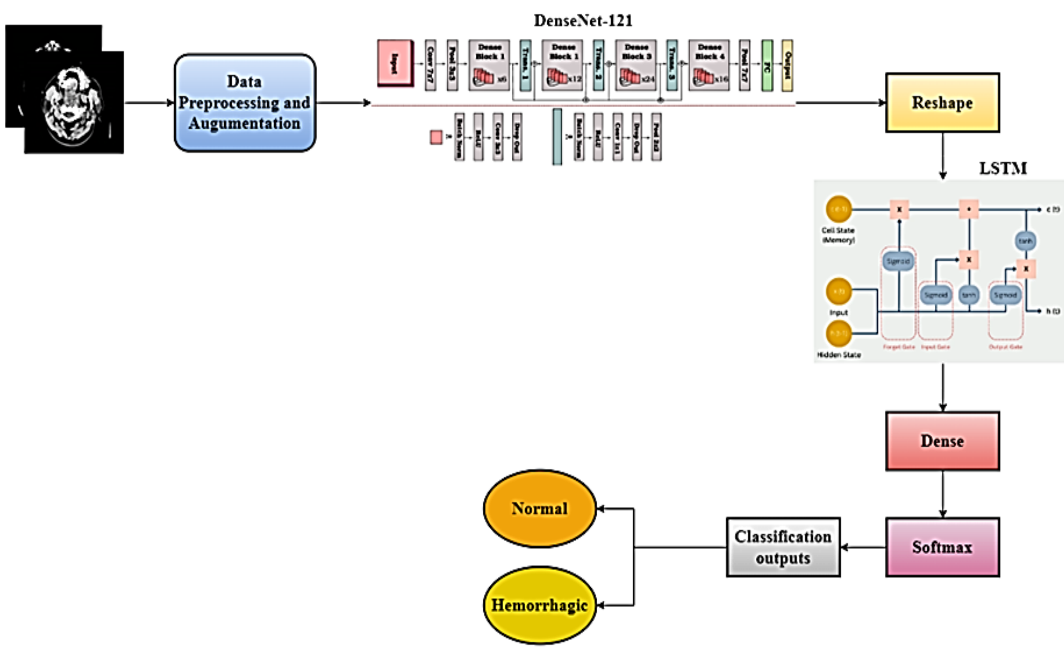

Fig. 1. Block diagram of proposed model.

A. Dataset Description

The dataset required for the classifying ICH from CT images is obtained from the Kaggle repository [20]. It contains images of normal and hemorrhagic CT scans collected from the Near East Hospital, Cyprus. It is having a total of 2600 images. The dataset consists of two folders each for testing and training. Again, each folder is further divided into two groups as “normal” and “hemorrhagic”. A total of 1600 images were used for training, 600 images for testing, and 400 images for validation. Fig. 2 depicts the sample images from the dataset.

B. Data Preprocessing and Augmentation

In the classification of ICH from brain CT images, preprocessing and augmentation plays an essential role in increasing the performance of the DL models. These processes standardize the input data through techniques such as resizing, normalization, and contrast adjustment to standardize the input data, ensures that the suggested model can effectively learn and generalize from the images. In this study the ‘rescale’ parameter normalize the pixel values to a range between 0 and 1. Data augmentation enhances the training dataset’s variability by applying random transformations like shearing, zooming, horizontal and vertical flips, and random rotations up to 30 degrees. These augmentations are applied to the input images during the training process, enhancing the diversity of the dataset and promoting better generalization of the deep learning model improving its ability to classify normal and hemorrhagic CT scans accurately. To separate the dataset into training sets and testing sets, an 80:20 ratio is employed.

C. Proposed Methodology

1) DenseNet 121: DenseNet is a CNN architecture where two layers are interconnected to all other layers deeper in a network. This is designed to allow the greatest flow of data among network layers. Firstly, it adopts a dense block structure, ensuring each layer connects to every other layer in a feedforward manner. Secondly, it incorporates bottleneck layers, which effectively decrease the parameter count while preserving the number of learned features within the network. As of Fig. 3 the DenseNet 121 consist of 121 layers and is characterized by its three main building blocks such as transition layers, dense blocks, and global average pooling layer [21].

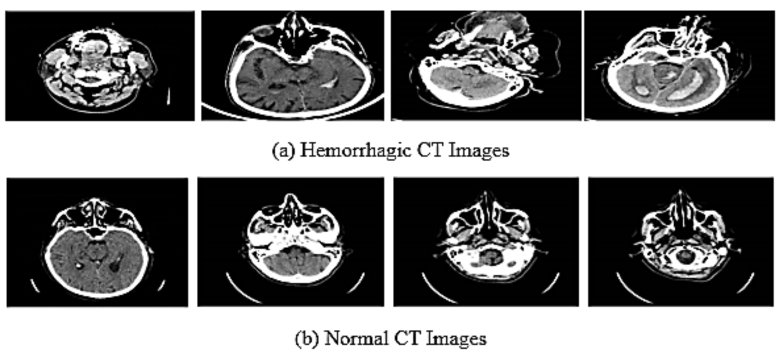

Fig. 2. Sample images from the dataset.

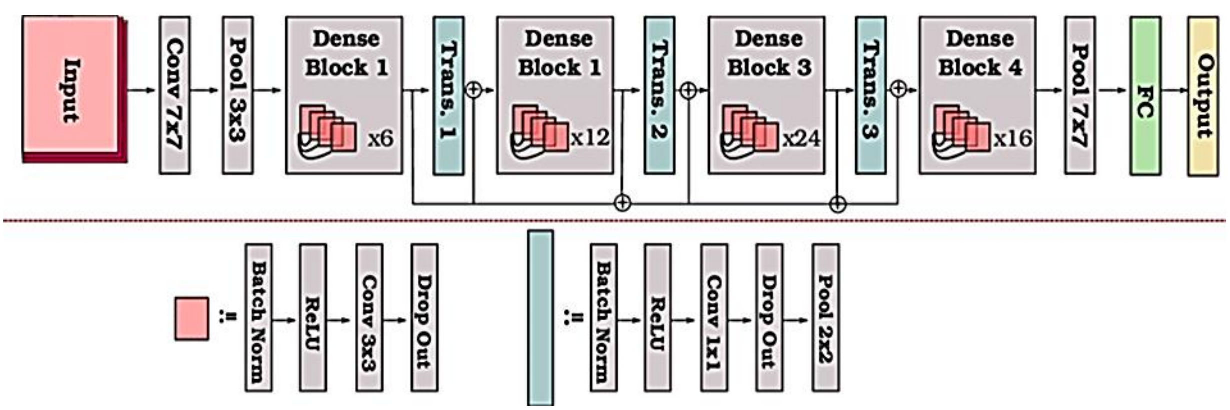

Fig. 3. Basic architecture of DenseNet 121.

In this architecture, the layers are connected through dense blocks, allowing each layer to utilize input from all preceding layers. This enables the creation of feature maps that propagates data to all subsequent layers. Each Dense blocks consist of several layers, composed of batch normalization, ReLU activation function and convolution. Let’s denote the output of the t^{th} layer as m_t where all previous feature maps are received as inputs. It is expressed as:

$$m_t = H_t([m_1, m_2, \dots \dots \dots \dots \dots \dots \dots .. m_{t-1}]) \quad (1)$$

Where, $[m_1, m_2, \dots \dots \dots \dots \dots \dots \dots .. m_{t-1}]$ represents the concatenation of feature maps from the t^{th} layer and H_t

represents the t^{th} layer, it's a sequence of three successive operations forming a composite function.

DenseNet 121 incorporates four dense blocks, with transition layers scattered between each block. These transition layers facilitate down-sampling of the feature maps by implementing a 1 x 1 convolution followed by a 2 x 2 average pooling layer. If the input to a transition layer is m, the output is given as,

$$m_{trans} = AvgPool(Conv(m, \theta, 1 \times 1) \tag{2}$$

Here, θ represents the reduction factor utilized to decrease the feature maps size.

The dense block comprises multiple convolutional layers interconnected in series, facilitating cross-layer connections between distant layers. DenseNet 121 utilizes the ReLU activation function to enhance the non-linearity of the frame work. The ReLU function defined as follows,

$$ReLU(m) = \max(0, m) \tag{3}$$

The final layer contains a fully connected layer followed by a softmax function, which is utilized for predicting the probability of the CT image class. The softmax function specified as follows:

$$sm(v)_i = \frac{e^{v_i}}{\sum_{j=1}^{D} e^{v_j}} \; for\ i = 1\ to\ D \tag{4}$$

Here, $v = (v_1, \dots \dots \dots \dots, v_D) \in \mathbb{R}^D$. The input vector, v, undergoes exponential computation for each value of v_i. The output vector's sum $sm(v)$ is equal to 1.

2) Long short term memory (LSTM): LSTM is used to solve the vanishing gradient problem. The model integrates memory cells capable of storing and retrieving information from long sequences. The architecture consists of three gates shown in Fig. 4, namely input gate, output gate and forget gate. The information that needs to be deleted and that needs to be kept from the previous stages and current input are determined by the forget gate. These values are then passed into a sigmoid function, that provide output values between 0 and 1, shows that if all previous information is lost, then the value is 0, and if all previous information is preserved, then the value is 1. The input gate determines the significance of the current input necessary for solving the task. Finally at the output gate, the model computes its output based on the hidden state. To perform this, sigmoid function determines which information should be allowed to pass through the output gate. After the decision, the cell state is activated with the tanh function and then undergoes multiplication [22].

The LSTM input at a particular time stamp *t*, is said to be (x_t) the data, (c_{t-1}) the cell state and $(h_{t-1}) \cdot c_{t-1}$ is the hidden state where h_{t-1} is the output in the previous time stamp. The three gates of the LSTM cell to control the flow of information are initialized as input gate (i_t), output gate (o_t) *and* forget gate (f_t). All gates utilize h_{t-1} and x_t as the inputs, employing the sigmoid function as activation function. The information stored at c_{t-1} is removed by the forget gate.

The forget gate is expressed as,

$$f_t = sigm(W_{fx}x_t + W_{fh}h_{t-1} + b) \tag{5}$$

For each current time stamp the learned representation is denoted by $\widetilde{c_t}$. Subsequently a point wise multiplication is carried out to preserve essential information. Computing both the cell state (c_t) and input gate (i_t), the equations are termed to be.

$$\widetilde{c_t} = tanh(W_{gx}x_t + W_{ih}h_{t-1} + b) \tag{6}$$

$$i_t = sigm(W_{ix}x_t + W_{ih}h_{t-1} + b) \tag{7}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tag{8}$$

At the current time stamp, the LSTM cell output is denoted by the hidden state (h_t), which is utilized for making decisions. The hidden state determines by eliminating non-essential information that does not contribute to the decision at time stamp *t*. This can be achieved by utilizing the output gate (o_t). The expression for obtaining o_t and h_t are

$$o_t = sigm(W_{ox}x_t + W_{oh}h_{t-1} + b) \tag{9}$$

$$h_t = o_t \odot c_t \tag{10}$$

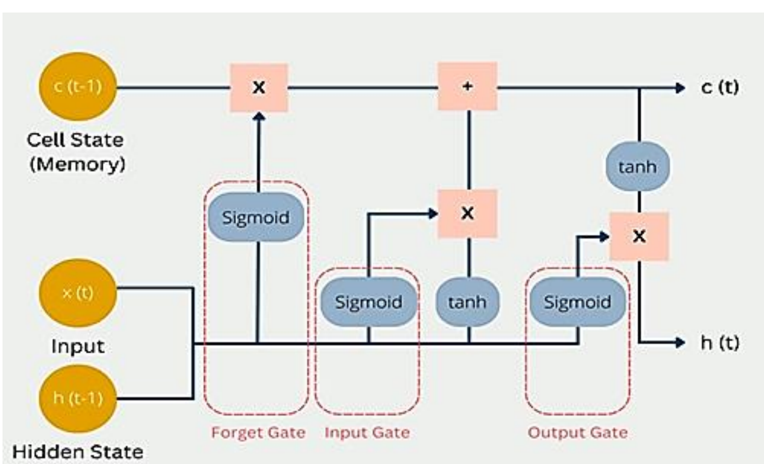

Fig. 4. Basic architecture of LSTM.

The proposed hybrid model combines the two-network architecture DenseNet 121 and LSTM. This combination utilizes the advantages of each architecture in capturing both spatial and temporal information's. The DenseNet 121 model serve as a feature extractor, capturing detailed spatial features from the CT images. These spatial features represent information about the structure and content of the images. In this case the LSTM model is employed to obtain temporal connections within the data, which could be important for analyzing how features change over time or sequence within the images. After extracting the spatial and temporal features, the model uses a dense layer with a softmax function as the output layer. The softmax function converts the output of the previous layers into probability scores corresponding to each class. The model performs binary classification to the brain CT images and further classified as "Normal" or "Hemorrhagic". Finally, the model's performance is assessed using a range of metrics such accuracy, F1 score, recall, and precision. Fig. 5 illustrates the architecture of the proposed work, while Table I provides a summary of the proposed model.

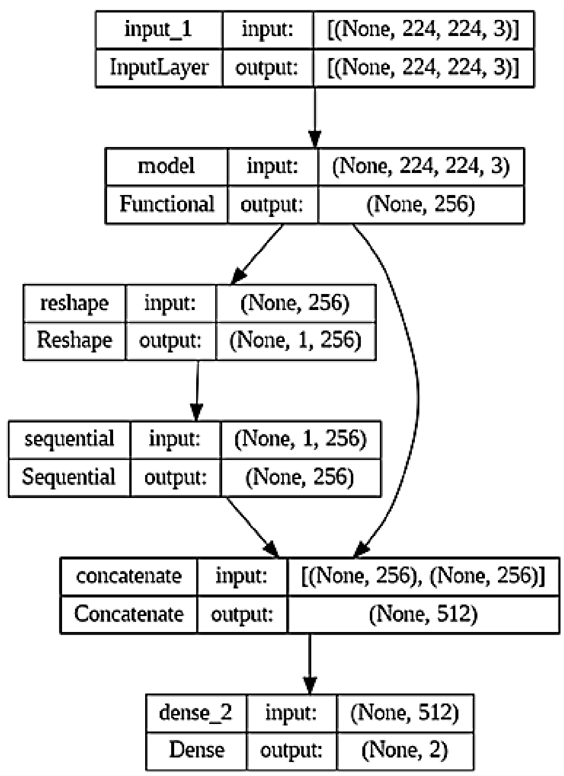

Fig. 5. Proposed model architecture.

TABLE I. SUMMARY OF THE PROPOSED MODEL.

Total Parameters	7531074
Trainable Parameters	7447426
Non-Trainable Parameters	83648

The proposed model algorithm is outlined below.

Algorithm

Input: Brain CT image dataset, labels determine Hemorrhage or Normal

Output: Predictions of whether the input image contains hemorrhage or not

Begin:

Load and preprocess data:

1. Collect dataset: C= $\{(A_i, b_i)$, where A_i is a brain CT image and $b_i \in \{0,1\}$ b_i i$\in \{0,1\}$ (1: Normal, 0: Hemorrhage).
2. Preprocess:
   - Resize: $A_i \rightarrow A_i' \in R^{224\times224}$
   - Normalize: $A_i' \rightarrow \frac{A_i'-\mu}{\sigma}$
   - Data Augmentation: $A_i' \rightarrow \{A_i''\}$(Shear, Zoom, Flipp (horizontal and vertical), Rotation)

Define Base Models:

1. Load Model: DenseNet 121
2. Input: $224 \times 224 \times 3$

   Global Average Pooling 2D ()

   Dense (256, activation='relu')

   LSTM (128)

   Dense (256, activation='relu')

   Concatenate ()

   Dense (2, activation='softmax')

Model Compilation and Training:

1. Compile each model M:

   Optimizer=Adam ()

Loss=binary _crossentropy
Metrics=[accuracy]

2. Train: M.fit (X_{train} , y_{train} ,validation_data= (X_{val}, y_{val}))

Model Evaluation and Comparison:

1. Evaluate:
metrics=M.evaluate(X_{test} , y_{test}), where metrics include accuracy, precision, recall.

Save the Model:

End

IV. Results and Discussion

A. Software and Hardware Setup

The model development and training were carried out using Google Colaboratory, employing Python and the Keras framework throughout the entire process. The Colab notebooks were equipped with TensorFlow, a GPU, 12.75 GB of RAM, 68.50 GB of disk space, and a 64-bit version of Windows 10. The efficiency of the model proposed was examined using its predictions on the test dataset. The hyperparameters of DNN are determined through empirical methods and significantly influence the learning process, as outlined in Table II. To identify the model that delivers the best classification performance, a wide range of variables are tested and evaluated.

B. Experimental Results

Accuracy and loss plots are utilized to visualize the effectiveness of a machine learning (ML) model throughout its training and validation phases. In the case of ICH classification from brain CT images, these plots offer valuable information on how well the model can differentiate between hemorrhagic and normal images. The accuracy plots illustrate the fluctuations in model accuracy across epochs during both training and validation. However, the loss plot shows the alterations in the loss function throughout the training and validation phases.

Fig. 6 and Fig. 7 show the accuracy plot and loss plot of the model. At the initial epochs the accuracy of the model is low suggest that the model is struggling to learn the patterns. However, as epoch progresses there is an improvement in the accuracy indicates the model is making correct predictions. This means that the model is correctly identifying images that contain signs of hemorrhage and those that are not. In some cases, there is a slight decrease in accuracy can occur due to fluctuations in training process or adjustments made to the learning rate. Similarly, the loss of the system is high at the initial epoch. As the epoch progresses the loss decreases steadily and towards the final epoch the loss become smaller indicates that the model is improving in its ability to differentiate between hemorrhagic and normal images. It is observed that when the learning rate decreases after a certain epoch it can affect the convergence of the model and lead to fluctuations in loss values.

TABLE II. Hyperparameter Specification

Hyperparameters	Values
Batch Size	64
Loss Function	Binary Crossentropy
Optimizer	Adam
Activation function	Softmax
Number of epochs	20

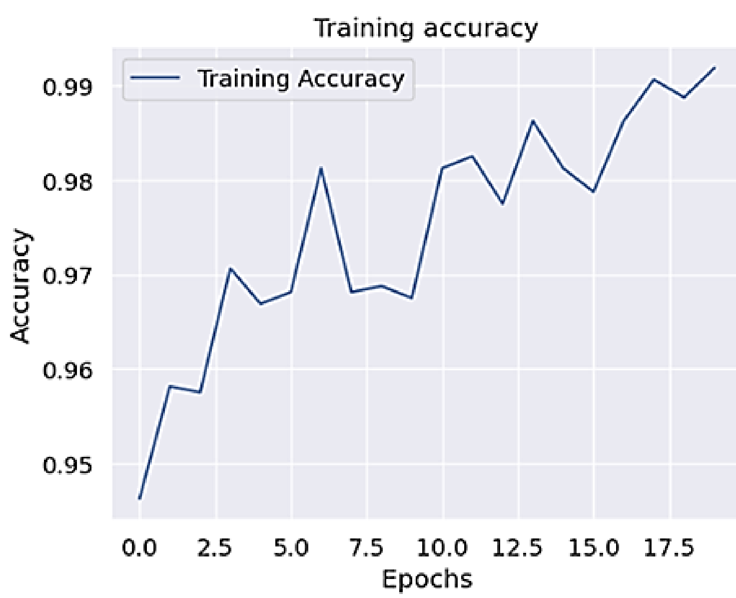

Fig. 6. Accuracy plot of proposed model.

Fig. 7. Loss plot of proposed model.

Evaluation metrics are essential tools used in measuring the performance of ML models, providing details about accuracy, reliability and generalization ability. Some of the common evaluation metrics used in the classification tasks.

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{11}$$

$$Recall = \frac{T_p}{T_p + F_n} \tag{12}$$

$$Precision = \frac{T_p}{T_p + F_p} \tag{13}$$

$$F1\ Score = 2 * \frac{(Recall * Precision)}{(Recall + Precision} \tag{14}$$

Where T_p is True Positive, T_n is True Negative, F_n is False Negative and F_p is False Positive.

The performance of the model is impressive with an accuracy of 97.50%, indicating overall correctness in its predictions. The precision signifies a low false positive rate at 97% highlighting the potential of the model to accurately determine positive instances. Additionally, 95.99% of recall suggest that the model accurately captures a significant portion of actual positive instances. The balanced F1-score of 96.33%, reflects a harmonious combination of recall and precision, reinforcing the model's robustness in handling both false positives and false negatives. Table III shows the proposed model's classification report.

TABLE III. CLASSIFICATION REPORT OF PROPOSED MODEL

Performance Metrics	Obtained Results
Accuracy	97.50 %
Precision	97.00 %
Recall	95.99 %
F1-Score	96.33 %

The efficacy of a classification algorithm is evaluated using a confusion matrix. Fig. 8 visualizes the classification of the ICH from brain CT images. It helps the model to correctly identify hemorrhagic and normal images. It analyzes the types of errors made such as missed hemorrhages and refine the model to improve the diagnostic accuracy. Ensuring reliable and effective medical diagnosis. In this confusion matrix, 295 images were correctly predicted as Hemorrhage, while 277 images were correctly predicted as Normal. Additionally, 25 images were misclassified as Hemorrhage, and three images were misclassified as Normal.

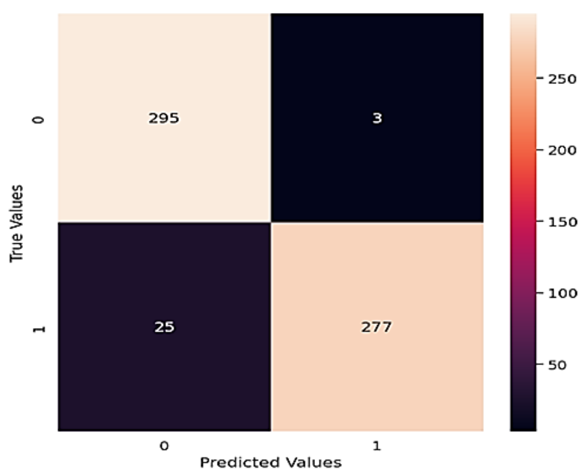

Fig. 8. Classification report of proposed model.

A randomly selected image from the dataset is classified using the suggested model, correctly classifying it as either "Normal" or "Hemorrhage.". As seen in Fig. 9, this successful classification highlights the efficiency of models and reliability in precisely identifying and classifying images within the dataset. Table IV presents a comparison of the accuracy between the proposed and current techniques.

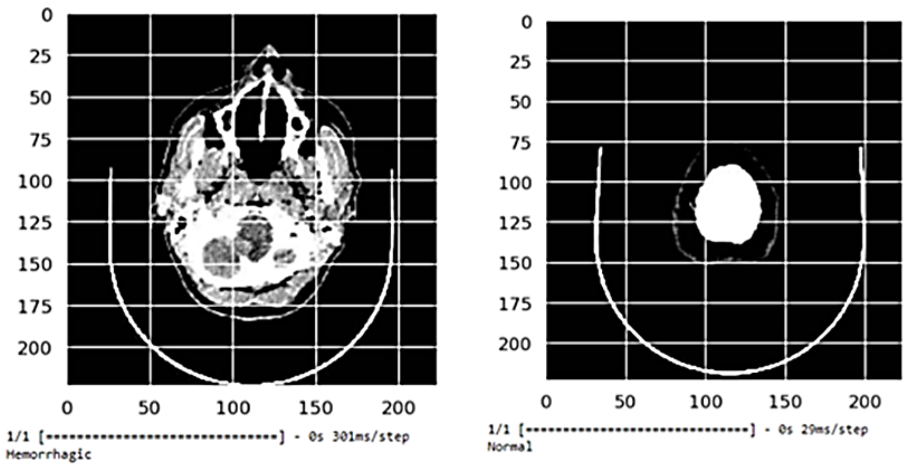

Fig. 9. Classification outputs.

TABLE IV. COMPARISON OF PROPOSED METHOD AND CURRENT APPROACHES

Sl. No:	Author	Methodology	Accuracy	Precision	Recall	F1 Score
1.	Rajagopal et al. [2]	CNN and LSTM	95.14	95.21	93.87	-
2.	Tharek et al [4]	CNN	95.00	93.14	92.94	95.00
3.	Anupama et al. [8]	Deep Learning	95.73	95.79	94.01	-
4.	Mansour and Aljehane [12]	Inception V4	95.06	95.25	93.56	-
5.	Venugopal et al. [23]	DL	96.56	96.43	95.65	-
6.	Qui et al. [24]	U-Net	94.1	93.5	95	-
7.	**Proposed Hybrid DenseNet 121- LSTM**		**97.50**	**97.00**	**95.99**	**96.33**

C. Discussion

Fig. 10 compares the accuracy of various models used for intracranial hemorrhage classification from brain CT images. The proposed hybrid model, which combines DenseNet121 and LSTM, achieves the highest accuracy at 97.50%. In comparison, a hybrid approach combining CNN and LSTM shows an accuracy of 95.14%, while a model using only CNN attains 95.00%. A deep learning model reaches an accuracy of 95.73%, and one using the Inception V4 architecture achieves 95.06%. Another deep learning model (DL) records an accuracy of 96.56%, and a model utilizing U-Net achieves 94.1%.

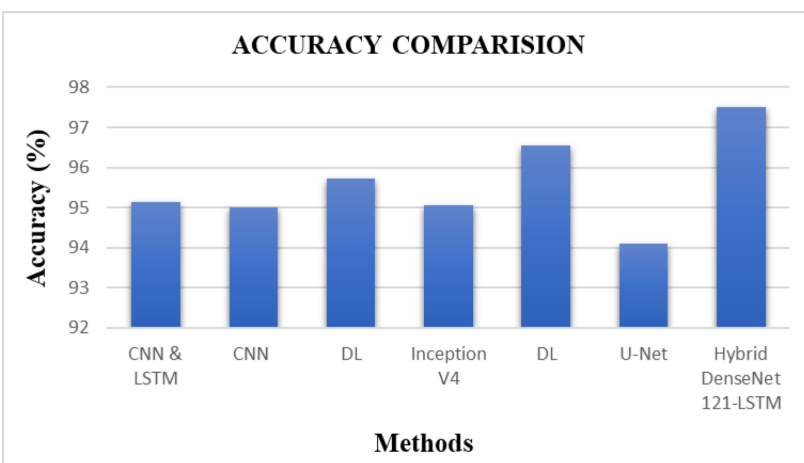

Fig. 10. Accuracy analysis of DenseNet 121-LSTM method with existing approaches.

Fig. 11 compares the precision of different models used for ICH classification from brain CT images. The proposed hybrid model, combining DenseNet121 and LSTM, achieves the highest precision at 97.00%, indicating its superior ability to accurately identify positive instances with minimal false positives. In comparison, the hybrid CNN and LSTM approach shows a precision of 95.21%, while a model using only CNN records a precision of 93.14%. A deep learning model achieves a precision of 95.79%, and the Inception V4 architecture reaches 95.25%. Another deep learning model (DL) shows a precision of 96.43%, and a U-Net model achieves 93.5%.

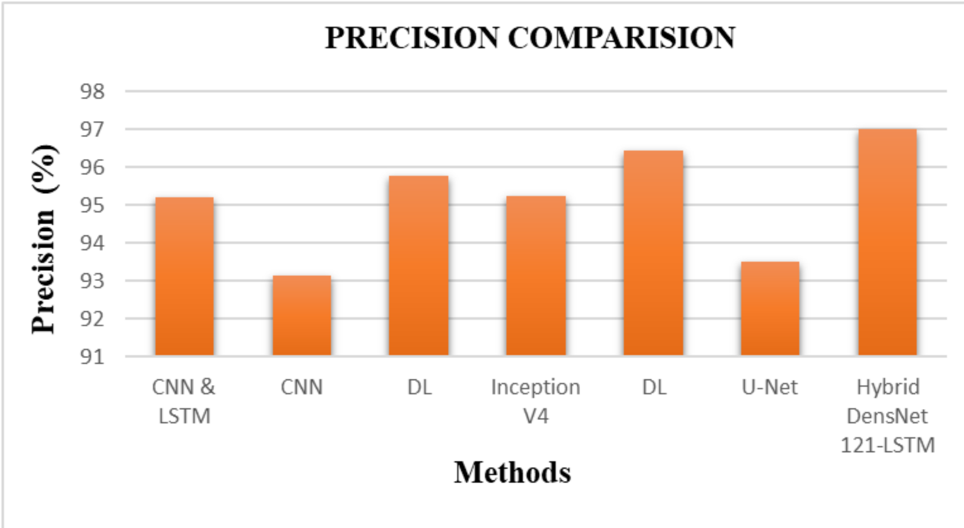

Fig. 11. Precision analysis of DenseNet 121-LSTM method with existing approaches.

Fig. 12 compares the recall of various models used for intracranial hemorrhage classification from brain CT images. The proposed hybrid model, combining DenseNet121 and LSTM, achieves a recall of 95.99%, indicating its effectiveness in correctly identifying a high proportion of actual positive cases. In comparison, the hybrid CNN and LSTM approach shows a recall of 93.87%, while a model using only CNN achieves 92.94%. A deep learning model records a recall of 94.01%, and the Inception V4 architecture reaches 93.56%. Another deep learning model (DL) shows a recall of 95.65%, and a U-Net model achieves recall at 95%.

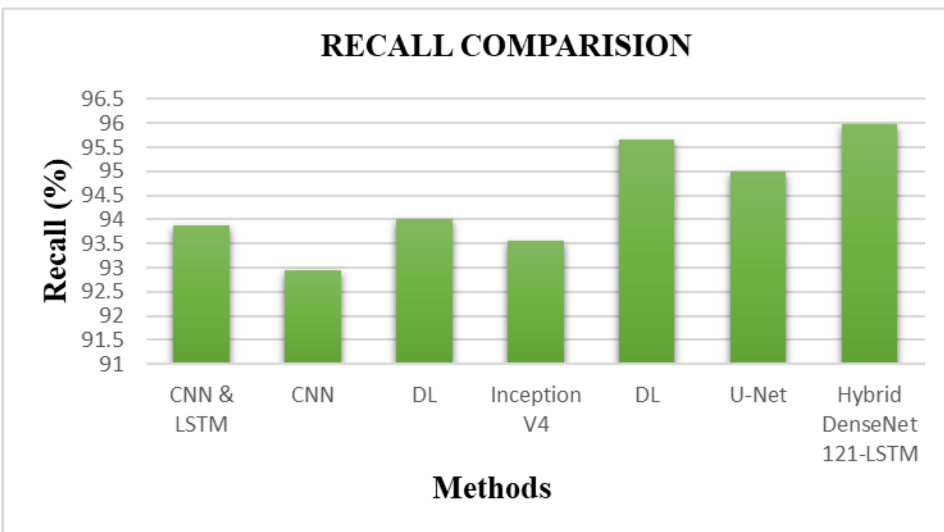

Fig. 12. Recall analysis of DenseNet 121-LSTM method with existing approaches.

V. Conclusion

ICH refers to acute bleeding inside the brain or skull. It is a serious condition that can results in severe disability or death. It is occurred due to a variety of factors such as trauma, vascular disease or congenital development. As a result of the severe compression caused by excessive bleeding, oxygen-rich blood is unable to flow to the brain tissue. AI-driven disease prediction can be used to identify individuals who are at higher risk of developing a certain disease, which can help inform decisions about preventative care and early intervention. This method uses a new hybrid DL based model for the classification of ICH from brain CT images. The model utilized DenseNet 121 and LSTM for accurate classification of ICH. The model demonstrates better performance exhibiting 97.50% accuracy, 97% precision, 95.99% recall and 96.33% F1 score highlighting its effectiveness and potential to improve diagnostic accuracy and patient outcomes in the detection and classification of ICH. A real time ICH detection and classification framework will be implemented in future.

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