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Brain Haemorrhage Detection using LSTM, Convolution Neural Network and CT Scan Images

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ABSTRACT- A brain hemorrhage is an eruption of the brain's arteries brought on by either excessive blood pressure or blood coagulation, which may result in fatalities or serious injuries. It is the kind of medical emergency that requires a clinician to quickly identify the site of internal bleeding before beginning therapy. Convolutional Neural Network (CNN) and CNN + LSTM hybrid models for deep learning are suggested in this study for the categorization of brain hemorrhages. The 200 head CT scan images dataset is utilized to increase the deep learning models' precision and processing capability. Because big datasets are rarely immediately available in essential situations, the main goal of this work is to apply the abstraction capability of deep learning on a smaller amount of pictures A unique architecture called Brain Haemorrhage Classification based on Neural Network was made utilizing the CNN model together with picture augmentation and dataset misbalancing approaches. The performance of the recommended technique is assessed using accuracy, precision, sensitivity, specificity, and F1-score. The experimental results are further evaluated utilizing comparative analyses of the balanced and unbalanced dataset using CNN and CNN + LSTM. Unbalancing the dataset yields encouraging results, outperforming CNN in accuracy. The results show the effectiveness of the proposed method for quick implementation in real-world circumstances and precise prediction to preserve the patient's life in the interim.

KEYWORDS- Convolution neural network. Haemorrhage, LSTM, CT scan.

I. INTRODUCTION

A medical word for bleeding within or outside of the body is hemorrhage [1], [2]. Brain hemorrhage is the medical term for internal bleeding in the brain [3]. This is brought on by an unexpected blood clot [4] in the arteries that provide blood to the brain or internal bleeding in the brain's perivascular tissues as a result of artery ruptures [5]-[8]. The most frequent causes [9] of this bleeding, which caused damage to the brain cells, are trauma [1], high blood pressure [10], aneurysms, anomalies of the blood vessels, amyloid angiopathy, bleeding diseases, and brain tumors [2]. These are the main reasons people die and become severely disabled. In 2013, brain hemorrhages were the cause of 30% of fatalities in the United States, with a ratio of 100,000:7 in the west and 100,000:200 in Asia [4]. In addition, women are more affected than men by the 3:2 ratio and the fact that 80 percent of babies have weak spots in their brain arteries [5]. According to a World Health Organization (WHO) estimate [6], 15 million individuals suffered strokes in 2009, of which 5 million died and 5 million were disabled.

Medical experts [7] emphasize the need of early diagnosis and effective first care in order to prevent disability and death in these situations.

Magnetic Resonance Imaging (MRI) [2] and Computed Tomography (CT) scans [9] may both show the internal architecture of the skull and brain, respectively. Medical experts prefer CT scans over MRIs for examining the inside architecture of the human body, particularly the brain, since it is more accessible, less costly, and sensitive to early diagnosis of brain hemorrhage. A computer using 3D imaging at various angles creates the cross-sectional X-ray images that make up a CT scan [1].. In order to capture tissues at different intensities depending on the extent of X-ray tissue absorption, the CT scanner transmits the X-ray [6], [2] beams in an arc. The CT scan provides comprehensive information on the internal organ tissues and skeletal structure, which helps doctors spot internal bleeding and blood clots in the brain [6]. The CT scan is frequently used in emergencies to detect infections, malignancies, serious injuries, and internal hemorrhagic strokes that are difficult for a person to notice [4], as well as other conditions [3]. The CT scan is chosen over the MRI for first treatment because it provides rapid acquisition. Because internal bleeding in the skull causes brain hemorrhages, identifying them is difficult [8]. Additionally, medical professionals need years of training to recognize the area of bleeding on a CT scan. Every single life is significant, and the lives of the sick are in danger. In earlier studies, researchers tried to create the ideal system to pinpoint the precise location of brain hemorrhage but failed due to flaws including diagnosis procedures taking too long and performance assessments showing insufficient results to save every patient's life. In Figure 1, CNN is used to classify brain hemorrhages.

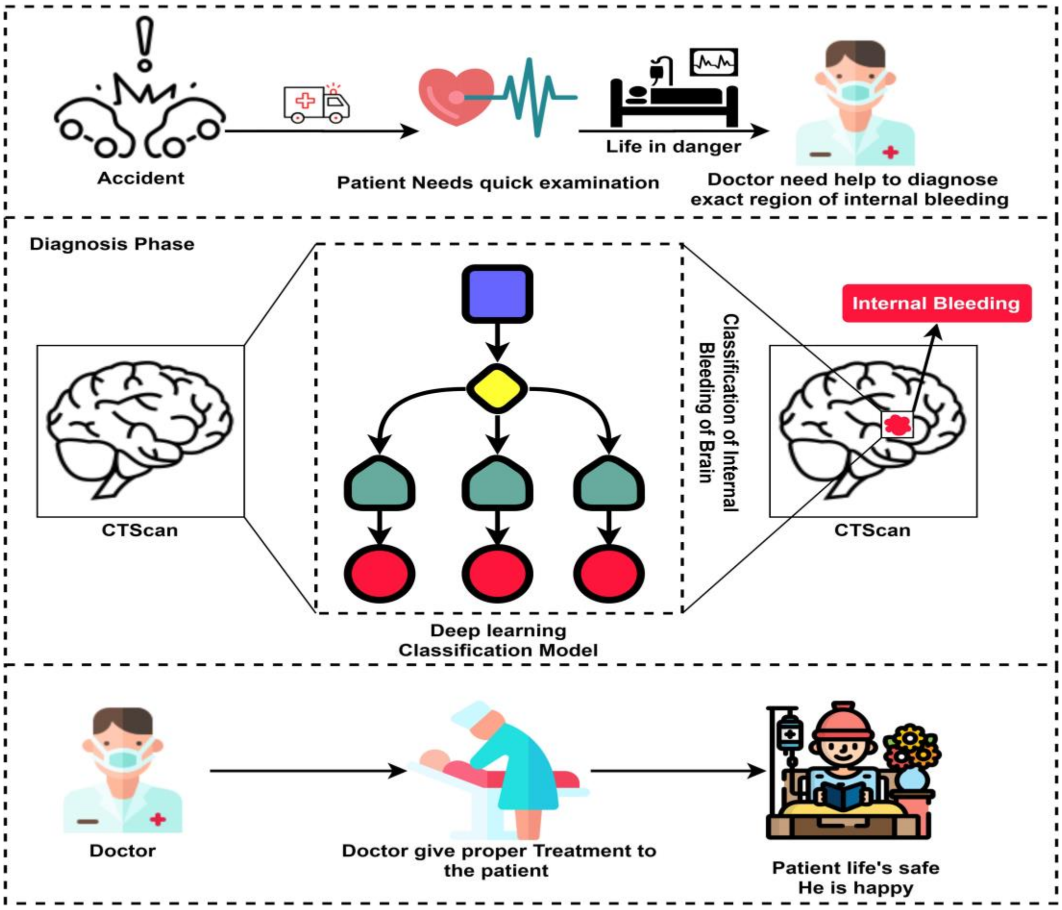

Figure 1: Brain hemorrhage classification using the CNN model to diagnose the region of the internal bleeding

The Different Types of Brain Hemorrhage Figure 1 suggests the usage of a Convolutional Neural Network (CNN)-based system to distinguish between brain hemorrhage and other disorders using pictures from a head CT scan. The system's innovative design boosts abstraction power, prediction speed, and accuracy by using a small dataset of 200 head CT scan images together with image augmentation and misbalancing approaches.

II. OBJECTIVES

- The recommended diagnostic strategy for those who have experienced a brain haemorrhage was created in the setting of sparse data and would be helpful in urgent circumstances where significant data are not immediately accessible.
- Deep learning models are used in the experiments, and image preparation methods such image scaling, image flipping, and image augmentation are used to increase the effectiveness of the training process and achieve the highest accuracy rate and performance of the CNN. CNN, hybrid CNN + LSTM is provided based on layered architecture and head CT scan images. The layer structure consists of convolutional layer, max-pooling layer, global average pooling layer, and dense layer.
- The efficacy of the proposed study is evaluated using the accuracy, precision, awareness, specificity, and F1 score performance assessment matrices. To evaluate the recommended method with experimental results, several experiments using hybrid deep learning models with balanced and unbalanced datasets are carried out.

III. LITERATURE REVIEW

Recently, neural networks have become increasingly routinely employed to create intelligent systems for identifying and treating health conditions. The machine learning [4] and deep learning [8] approaches were created in prior research [9], for the automated diagnosis of a brain haemorrhage. Several writers have recommended categorizing brain haemorrhages into different groups using different methods.

MRI [1] and CT scan [2], [3] were used to ascertain whether or not the patient had brain haemorrhage. Naive Bayes [4], K-Means clustering [5], Image Segmentation [6], Multi-Class Classification [7], Recurrent Neural Network (RNN) [8], Long Short-Term Memory (LSTM) [3], CNN [4], and Hybrid Models [4] were used to classify the brain haemorrhage. Both the little dataset and the large dataset are used by many authors to support their conclusions. Deep learning methods were utilized to categorize brain haemorrhages using a Computer Tomography (CT) [9] scan.

Utilizing deep convolutional neural networks and auto-encoders, which rely on three hidden layers, this study achieved increased recognition rates of 89.6% with CNN, 90.96% with stack autoencoder, and 0.0021 with stacked auto encoder compared to 0.099 with CNN using the characterisation curve. This technique is more difficult and time-consuming since it uses a larger dataset and has to run for a longer period of time (12000 iterations).

IV. METHODOLOGY

A CT scan may quickly and accurately identify internal bleeding, serious wounds, and distorted veins in the body that cause strokes or death. 200 equally spaced CT scan images from people with and without brain hemorrhages are included in the collection.

There are 100 CT scan images of patients with non-brain hemorrhages. The two categories in this labeled dataset are hemorrhage elsewhere and hemorrhage in the brain. Images are made up of different heights and widths, as seen in Figure 2, which shows the various variances in visuals. The CNN model's training process is accelerated by this small dataset's numerous benefits, which also reduce the risk of overfitting... Although this small dataset has certain benefits, such accelerating CNN model training and reducing the risk of overfitting, it also reduces accuracy rate, which is the problematic part. This is the reason why the study's use of this dataset proved successful. Prior to preprocessing, this dataset has to be focused on in order to improve accuracy. While Figure 3 shows the visualization based on the variation in image density, Figure 2 shows the visualization of the CT scan image dataset based on the variation in image height and width. CNN models are unable to learn since they need a certain amount of input data. Figure 2 shows the noise in the images, which is a distortion based on density, in relation to height and width.

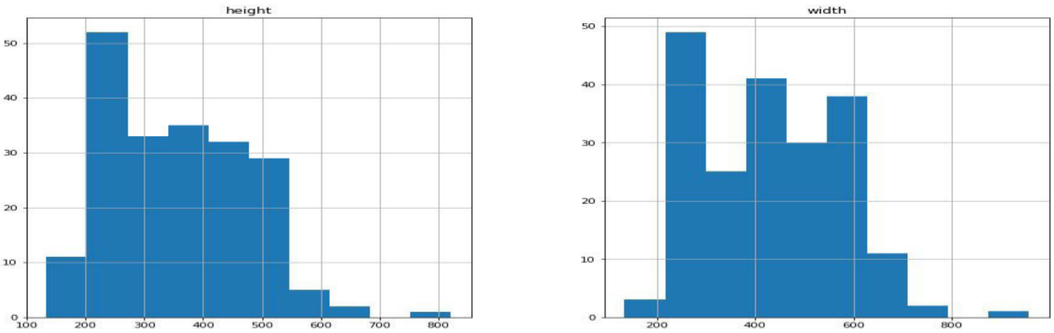

Figure 2: The CT scan image dataset visualization based on variation in dataset

A. Preprocessing

Since it's crucial to appropriately diagnose a brain hemorrhage in the medical field, the suggested study primarily focuses on the CNN model's learning phase. The CT scan image dataset needs further attention based on various filters and upgrades in order to increase the learning efficacy of the CNN model's training phase. To enhance the performance of deep learning models, preprocessing entails filtering, reshaping, and quality improvement of the dataset. In this study, several approaches including resizing, flipping, and photo augmentation are used to enhance the quality and quantity of the image data.

B. Resize the Images Data

The same-sized pictures must be used to train the deep learning models. By reducing the images to the same sizes, learning is hastened, and the chance of overfitting is diminished. Data loss happens throughout the scaling process, which has an impact on the model's performance and accuracy rate. This is one of the challenging parts of scaling the image data. The study proposal involves resizing the images in a fixed size of 128 128 dimensions. It is successful in addressing the issues of overfitting and quick learning since it has the greatest accuracy rate.

C. Training and Testing Data Split

The train-test split refers to the process of dividing data into a predetermined ratio for developing and evaluating deep learning models. The fact that a brain hemorrhage is a medical emergency is the most important factor in making an accurate diagnosis. After extensive data training, the deep learning models must provide precise predictions. 90% of the data were selected for the training phase, while only 10% were picked for the testing phase. There are a total of 200 images, 100 of which feature people who have experienced non-brain hemorrhages. Out of the 180 photos used for the training, 90 randomly selected photos from hemorrhage and 90 randomly selected photos from hemorrhage that didn't involve the brain were picked... The remaining 20 images were tested, with 10 originating from hemorrhage and the remaining 10, as shown in Figure 3, from hemorrhage that did not affect the brain. After that, picture augmentation was used to enhance what the 180 training images taught the deep learning models.

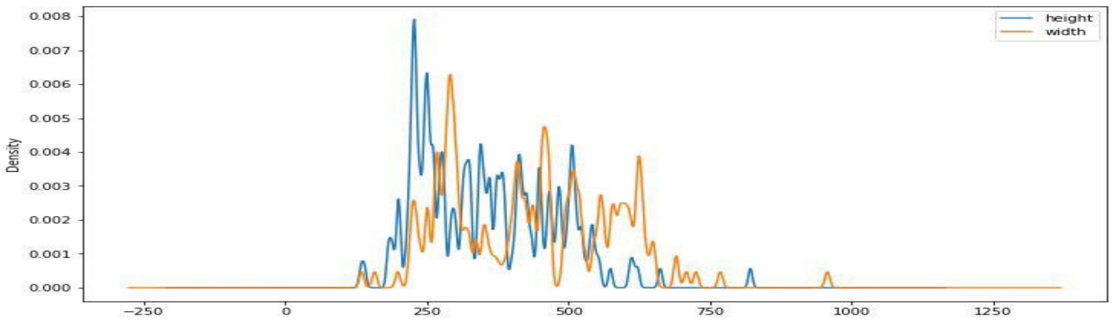

Figure 3: The CT scan image dataset visualization is based on variation

D. Image Augmentation

Picture augmentation is the process of adding data artificially to improve learning and prediction accuracy [1]. The greatest obstacle to learning deep learning concepts is a small dataset [2]. As a result, the training and validation datasets are artificially enhanced using picture augmentation techniques including flipping, rescaling, shearing, adjusting the zoom level, rotating the image at different angles, modifying the width or height ranges, and using fill mode. To treat each image equally because the picture collection comprises images with various pixel values, all of the photos' pixel values were changed to fall between (0, 255) and (0, 1). By zooming at a range of 0.05, shearing counterclockwise, moving the range of the image height and breadth at a range of 0.05, and filling mode at constant, the picture augmentation approach enhances the little dataset for the training process.

V. SYSTEM ARCHITECTURE

Enhancing classification performance, prediction speed, and deep learning model training are the main objectives. If the patient has a brain bleed or not, it may be determined using a dataset of 200 CT scan images. By increasing the dataset from 180 training shots to 1000 images utilizing image augmentation techniques, the recommended approach solves all issues. To identify brain bleeding, deep learning models CNN and hybrid models CNN + LSTM are used. The Dell PowerEdge T430 graphic processing unit, which has 8 cores, 16 logical processors, and 32 GB of installed DDR4 RAM, is used to perform the experiments (RAM).

A. Training

The training of the CNN using the 1000 improved head CT scan dataset only took 21 minutes, in contrast to the hybrid models CNN + LSTM, which took an average of 22.4 minutes to run every epoch. The test results demonstrate how effectively the CNN model classifies data from a balanced dataset. Among the several assessment matrices employed, accuracy, precision, sensitivity, specificity, and F1-score are only a few. After implementation, studies give the results as TP, TN, FP, and FN, which stand for the model's precise and imprecise positive and negative predictions. Table 3 presents six alternate experiments depending on epochs. The best outcome was obtained using 24 epochs and had a 95.23 percent F1-score, 90.90 percent precision, 100 percent sensitivity, and 95.3 percent accuracy rate. Rates of true positives (TP) are 10%. The CNN model accurately predicted that 10 of the patients will develop a brain hemorrhage, hence this amounts to 10 successful predictions. The CNN model successfully predicted 9 individuals with non-hemorrhage diagnoses who in fact had non-brain hemorrhages out of the 20 test cases, according to the true negative (TN) rate, which stands at 9.

Now, a false positive (FP) of 0 denotes that the CNN model anticipated that the patient would experience a brain bleed, but the actual outcome was also 0. This study's main objective is to locate the last false negative (FN) instance, which occurs when FN is 1. It shows that even while the CNN model was unable to detect or predict the one patient's internal head hemorrhage.

. It would be considered a cause of death since the doctor decided to treat the patient differently as a result of the incorrect forecast. In this case, there are 1 FN incidences as a result of inaccurate prediction, which means 1 patient is in immediate risk. The 95% accuracy of the CNN model is not enough to save every single patient. Our investigation indicated that the data should be seen as imbalanced as a result. Figure 4 is the most effective display of the average results produced using 24 epochs.

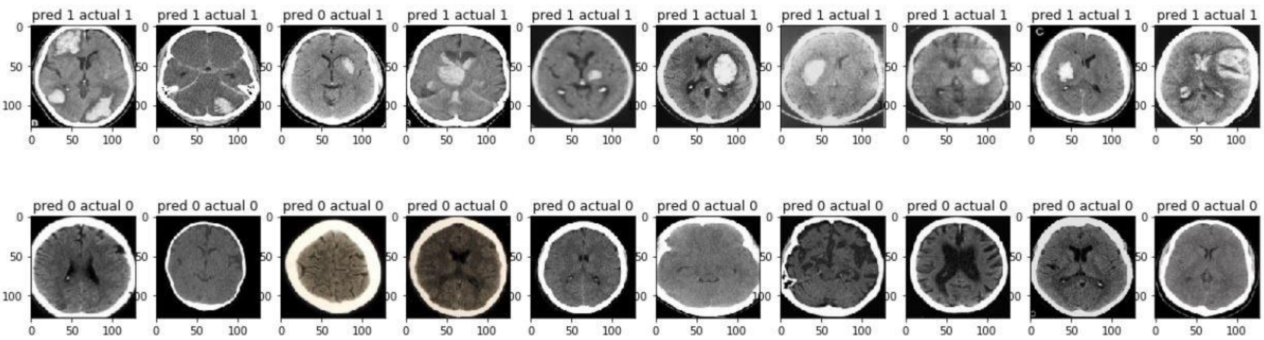

Figure 4: Average 24 epochs

There, the advancement of the CNN model is step-by-step shown for each epoch. Based on actual and anticipated findings, Table 1 is showing the experimental results of CNN model with balanced dataset. There are 20 test brain CT images with the labels Pred (Predicted) and Actual, where (1) depicts the patient with a brain hemorrhage and (0) depicts the patient without one. The parallels between the anticipated and actual results show that the conclusions are accurate. Internal bleeding is also seen as some gery-white spreading in the CT picture in both the predicted and genuine (1) situations.

Table 1: Experimental results of CNN model with balanced dataset

Ep.	TP	TN	FP	FN	Accu.	Prec.	Sensi.	Speci.	F1-Score
04	7	9	1	3	80.0	87.5	70.0	90.0	77.77
08	8	8	2	2	80.0	80.0	80.0	80.0	80.0
12	1	10	0	9	55.0	100	10	100	18.18
16	10	8	2	0	90.0	83.33	100	80.0	90.90
20	10	8	2	0	90.0	83.33	100	80.0	90.90
24	10	9	0	1	**95**	**90.90**	**100**	**90.0**	**95.23**

where Ep. is number of Epochs, Accu. is Accuracy, Prec. is precision and Sensi. is Sensitivity Speci. is Specificity

The patient in instance (0) does not have a cerebral hemorrhage, according to the CT scan results, which show no signs of internal bleeding. Contrary to CNN's prognosis, the third result in the first row shows that the patient has a brain bleed. Actual. however, the outcomes are not the same as those anticipated. The results show that in the medical field, a 95% accuracy resulted in the death of one patient. The medical sector has to put more of an emphasis on making accurate diagnoses because a patient's mortality might be caused by a mistake. The recommended inquiry should pay more attention to the situation when a patient really has a brain hemorrhage, but the CNN model predicts a non-brain hemorrhage. The proposed CNN model, with its layered architecture and image augmentation, achieves accuracy of 95% despite using more sample images.

B. Imbalancing the Sheets

This study employs two strategies to tackle this issue.
The dataset has to be imbalanced in order to increase the number of positive cases before the CNN model can concentrate more of its training on FN occurrences.
For the subsequent iteration, keep the class weights from the model's first training.
The CNN model concentrates more on producing inaccurate predictions as a result of the dataset imbalance, which increases both the prediction and accuracy rates. The training data consists of 243 images after training and test data imbalance and 180 images after training and test data splitting from CT scans. Additionally, the experimental analyses are shown in Table 2 which shows the top results with 12 epochs, including a 95.5 percent specificity, a 100% accuracy rate, a 100% sensitivity rate, and a 95% F1-score. These results assume that TP, TN, FP, and FN are respectively 10, 10, 0, and 0.

Table 2: Proposed BHCNet experimental results using CNN model with imbalanced dataset.

Ep.	TP	TN	FP	FN	Accu.	Prec.	Sensi.	Speci.	F1-Score
04	10	7	3	0	85.0	76.92	100	70.0	85.0
08	10	9	1	0	95.0	90.90	100	90.0	95.23
12	10	10	0	0	**100**	**95.54**	**100**	**100**	**95.0**
16	9	10	0	1	95.0	100	90.0	100	94.73
20	9	6	4	1	75.0	69.23	90.0	60.0	78.28
24	10	9	1	0	95.5	90.90	100	90.0	95.23

where Ep. is number of Epochs, Accu. is Accuracy, Prec. is precision and Sensi. is Sensitivity Speci. is Specificity

The highest accuracy of 100% was reached by deleting all inaccurate predictions and improving the CNN model's learning. by generating an uneven dataset for the tests and saving the class weight for further processing. Table 3 displays Comparative representation of results of proposed BHCNet, CNN, hybrid model CNN C models with balanced and imbalanced dataset. During the second experimental phase, the same set of layers and hyper-parameters are once more added to the CNN model. The prior class weights from the training phase based on epochs are kept and uploaded once again in order to increase training efficiency and training and accuracy rates.[10]
The difference The dataset provides the best support during the training of the CNN model. The elimination of inaccurate results like FP and FN is the main objective of this experimental phase since the patient's life is in jeopardy. The classification results of the CT scan pictures are shown in Figure 5, where each image is labeled with actual and predicted findings.

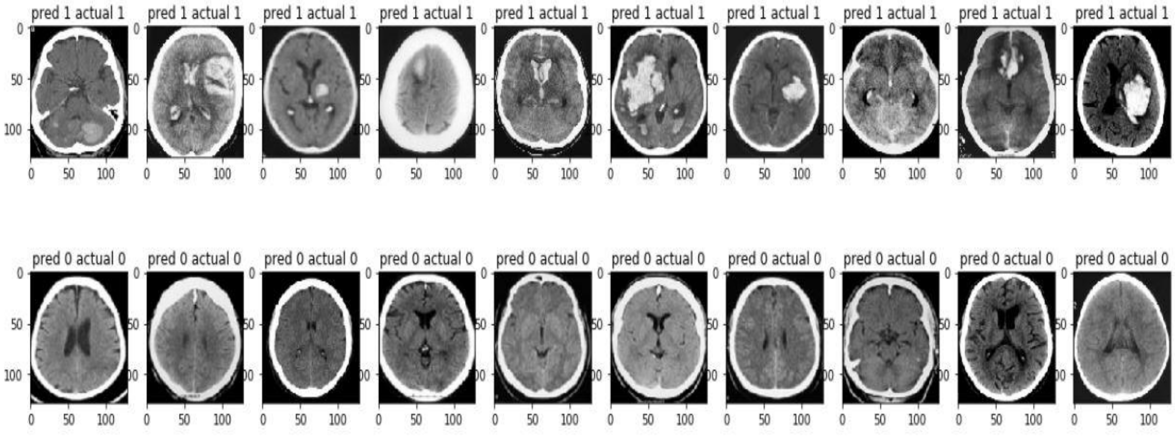

Figure 5: Comparative results of the hemorrhage and non-brain hemorrhage CT scan image classification using proposed systemt with imbalanced

There is no dissimilar outcome, indicating that the proposed study successfully matches predictions with actual labeling to forecast the difference between patients with and without cerebral hemorrhage. The best results occur, and all inaccurate predictions are successfully obliterated.

Table 3: Comparative representation of results of proposed BHCNet, CNN, hybrid model CNN C models with balanced and imbalanced dataset

Deep Learning Models	Accuracy	Precision	Sensitivity	Specificity	F1-Score
Proposed CNN with balanced dataset	95	90.90	100	90	95.23
BHCNet: Proposed CNN with imbalanced dataset	**100**	**95.54**	**100**	**100**	**95.0**
CNN+LSTM with balanced dataset	90	90	90	90	90
CNN+LSTM with imbalanced dataset	95	90	100	90	95.23

In order to evaluate the CNN model's training processes, model loss and accuracy validation are utilized. The term "epoch" refers to the number of iterations used during training to extract features and deliver them to next layers for learning. If accuracy of the model drops and losses increase throughout the training period, the model is not learning and shows overfitting. When accuracy increases and loss decreases, the model is said to be learning. Table 3 displays the accuracy and loss of the proposed CNN model for the train and test data. The best training accuracy is achieved during the training process with the least amount of data loss...

This indicates that by utilizing image augmentation techniques and the minimal layers of the CNN model, the speed and computing capacity of the proposed model is improved merely in 12 epochs. The outcomes are also reviewed to show how well the suggested study worked. Comparative discussion is held on the experimental outcomes of the CNN and hybrid CNN + LSTM models using balanced and unbalanced datasets.

C. Comparative Analyses of Results of CNN And Hybrid CNN + LSTM Model

The CNN model is utilized with LSTM a models because it contains memory cells and a gated mechanism. While CNN lacks a memory cell structure, LSTM can take sequential input, which increases the CNN model's learning effectiveness. The LSTM regulates the information flow in memory cells using input output and forget gates. Because it has fewer parameters than the LSTM model, the GRU model runs more quickly. The GRU has update and reset gates, however after CNN modeling, LSTM is introduced.

In contrast to CNN's accuracy of 90%, CNN + LSTM has a maximum accuracy of 95%. Table 5 compares the results of the proposed BHCNet, CNN, hybrid CNN + LSTM, and CNN + GRU models and plainly demonstrates that BHCNet performs best when CNN model uses data misbalancing strategy. The method outperforms the hybrid CNN + LSTM models by reaching 100 percent accuracy, 95 percent F1-score, 95.54 percent precision, 100 percent sensitivity, and 100 percent specificity. Table 6 further contrasts the proposed technique with past studies.

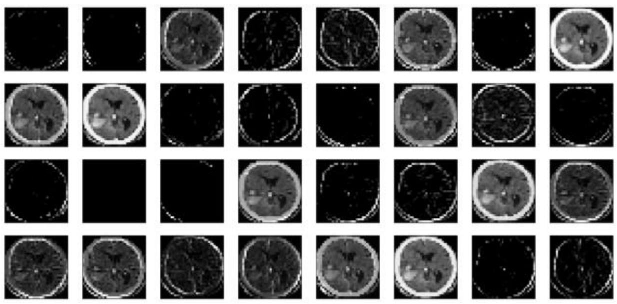

Figure 6: Visualization of the features

The comparative analyses display two major objectives that are successfully achieved.

The characteristics are visualized in Figure 6. The major objective is to offer a technique that may be used in emergency scenarios where large datasets are initially unavailable and model training with a small dataset is required. Since the bulk of authors and researchers recommend utilizing huge datasets, experiments are conducted using small datasets. In [4] and [6], large datasets were used. In contrast to the large dataset and intricate approach, we are releasing a simpler strategy that uses a smaller dataset and trains models faster.

The second goal is to help everyone who is being hurt by inaccurate diagnoses and careless medical procedures. To achieve this, prediction results must be enhanced. Furthermore, The main objective of research is to use neural networks in the most practical way by employing just their most fundamental and fundamental components. These essential elements are also required since they emphasize the importance of the proposed BHCNet. Each of its sophisticated applications, including LeNet-5, AlexNet, VGG, GoogleNet, and Residual Network or ResNet, has its own requirements, benefits, and limitations. The most fundamental approach used in these applications is the convolutional neural network (CNN). The first CNN application is LeNet-5 [7].

The primary selling point of the LeNet-5 is that it accepts input with a fixed size of 5 5 pixels using 16 filters. The filters get deeper as the network gets deeper. Krizhevsky et al. [79] suggested AlexNet, which was built to employ ReLU activation function for every convolutional layer instead of other traditional activation functions.

In AlexNet, half of the LeNet-5 layers are replaced by max-pooling layers, which are used to reduce the number of features by increasing the filter size and to handle overfitting. The dropout rate affects the fully connected layers in the final step. takes time for complex computations and a significant amount of data collecting for training.

The VGG proposal was made in 2014 by the Visual Geometry Group (VGG) at Oxford. The VGG consists of a substantial network of layers with between 16 and 19 layers, with dramatic repetition of the block of enormous convolutional layers set and max-pooling layers. It depends on the stride one's little size filters, though. Due to its depth and sizeable pre-trained model, the VGG is used as a starting point in transfer learning. GoogleNet is a parallel convolutional layered architecture proposed by Szegedy et al., consisting of 1 1, 3 3, 5 5, and 3 3 max-pooling layer filters of different widths. The output of these parallel layers is concatenated to create the inception module. The problem with the inception model is that the number of filters quickly grows as the inception modules are added. A huge network is produced as a consequence, consisting of around 22 layers, including extra convolutional and pooling layers, which need a substantial training dataset.

The output of the model was also used in a layer of global average pooling. ResNet was first presented by He et al. The key change is the short-cut connections with the deep 152-layer architecture, where the input is kept in its original form instead of being weighted and transmitted to the deeper layer after skipping the previous layer.

ResNet is a deeper network that houses enormous datasets and computationally taxing tasks. The primary contribution of this study is the recommendation of a neural network that can be used successfully for smaller datasets with a thin network of layers for a quick and accurate prediction rate to save the patient's life even in an emergency situation. Second, the CNN model known as BHCNet, which is designed to predict brain hemorrhage, is specifically trained and validated using images from brain CT scans. The third BHCNet was built using the minimum number of layers, shortest feasible filters, and hyperparameters.

The first two blocks of layers in this system are convolutional, while the third block is made up of a convolutional layer and a global average pooling layer. The convolutional neural network retrieves the pertinent feature with a filter size of 3 3 after the max pooling decreases the features for the net layers with a pooling size of 2 2. As shown in Figure 5, ReLU activation functions rather than only tan or linear activation functions with a 3 3 filter are employed to build convolutional layers. ReLU tackles the vanishing gradient difficulties with a dropout rate that controls the overfitting problem.

After looking at a previous CNN model application that utilized a larger training dataset and deeper networks, the strategy is generally recommended. In order to get the best and most accurate prediction results, we try to overcome challenges including overfitting, time consumption, accuracy, computation, complexity, and model depth. The main objective of this research is to develop a system that can accurately and quickly predict brain hemorrhages using a small dataset of CT scan images. As a consequence, the tests employing the advised method are successfully completed to resolve every problem. The proposed CNN model performs better than hybrid models and provides the patient with the most rapid and accurate diagnosis possible. The performance evaluation and comparative experimental results show how effective the recommended research is. Innovative deep learning and constrained dataset for key conditions are used in the study's methodology and strategy. like CNN

VI. RESULTS AND DISCUSSION

The dataset for the CNN+LSTM model was used for the research in this model. The model was trained using the optimize for 30 iterations, with a cosine annealing schedule and linear warm-up, with an initial learning rate of 1e-3.

Various classification methods, random cropping, random rotation between 0 and 30, random resizing, optical distortion, grid distortion, and Gaussian noise were used during training. Both the quality and the loss were kept and reported. For greater precision and less loss, the number of epochs was increased. Eventually, the top model was kept. Figure 7 to figure 12 show the accuracy and loss curves from epoch 1 to epoch 30.

A. Epoch 1

Accuracy : 60%

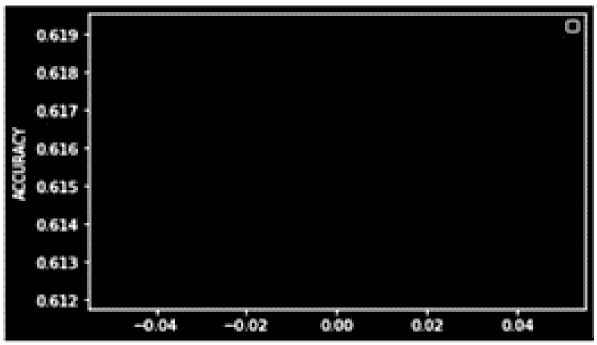

Figure 7: Accuracy curve on epoch 1

Epoch 1
Loss : 0.6703

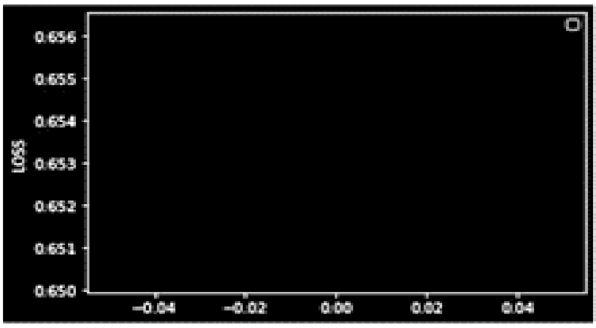

Figure 8: Loss curve of epoch 1

B. Epoch 5

Accuracy : 74%

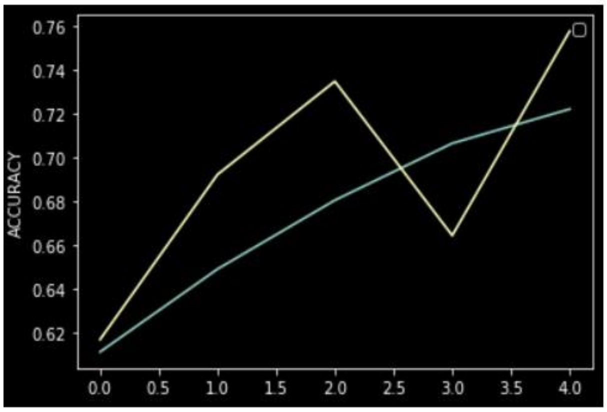

Figure 9: Accuracy curve of epoch 5

Epoch 5
Loss : 0.5270

C. Epoch 10

Accuracy : 74.71%

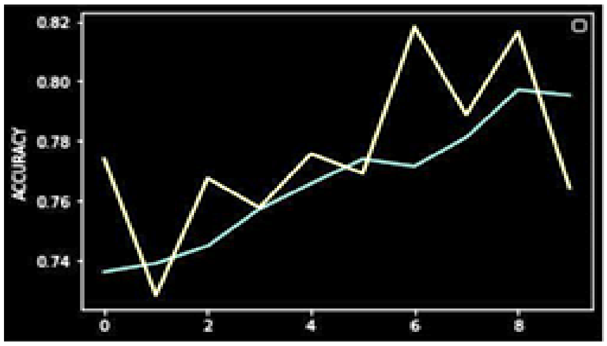

Figure 10: Accuracy curve of epoch 10

Epoch 10
Loss : 0.5039

D. Epoch 30

Accuracy : 93.53%

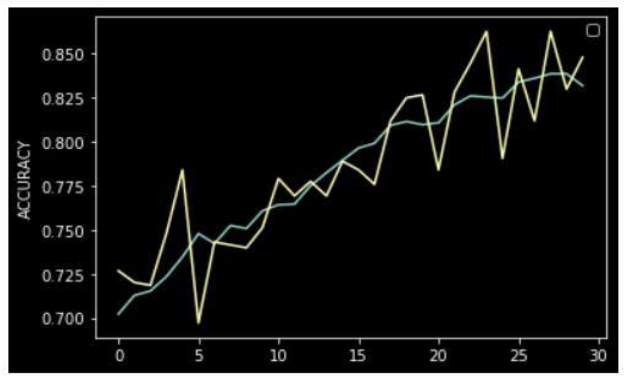

Figure 11: Accuracys curve of epoch 30

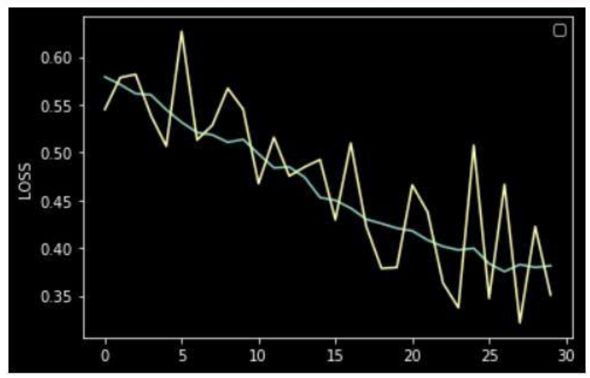

Figure 12: Loss curve of epoch 30

Epoch 30
Loss : 0.1794

In below table 5 is showing the previously applied approaches and table 6 is showing the the accuracy & loss results with different- different Epoch conditions.

Table 5: Analyses of previously used approaches with proposed approach

Literature	year	Dataset	Technique	Accuracy	Specificity	Precision	Sensitivity	F1-Score
[73]	2019	Large non contrast CT scan dataset	AlexNet-SVM	93%	90%	-	95%	-
[74]	2019	Large Head CT scan dataset	hybrid 3D/2D mask ROI-based CNN architecture	97.5%	97.5%	79.3%	97.1%	-
[75]	2019	Large dataset of non contrast CT scan	Aidoc (Tel Aviv, Israel) neural network software	Overall 93% in emergency cases 96%	94.2%	73.7%	88.7%	-
[76]	2019	Small dataset of Head CT imaging	CNN	91%	-	90.89%	93%	91.45%
[77]	2020	Large dataset of CQ500 head CT dataset	3D CNN	97%	94%	97%	98%	94%
Proposed BHCNet	**2021**	**Head CT scan Small dataset**	**CNN**	**100%**	**100%**	**95.54%**	**100%**	**95%**

Table 6: The results of the evaluated model

Epoch	Accuracy	Loss
Epoch 1	60%	0.67%
Epoch 5	74%	0.52%
Epoch 10	74.7%	0.5%
Epoch 30	93%	0.1%

VII. CONCLUSION

In order to detect brain hemorrhages, this study recommends utilizing CNN or a hybrid CNN + LSTM model for deep learning. By applying image augmentation, the training dataset is increased from 180 to 1000 images. The investigations employ both an equal and an uneven dataset. A balanced dataset with an equal number of classes for brain hemorrhage and non-brain hemorrhage was employed in the first experimental phase. The balanced dataset CNN used to achieve accuracy of 95% discloses the loss of one life as a result of: Types of Brain Hemorrhages Neural network use The CNN model employs a head CT scan and concentrates on the false-negative findings that show the patient truly has brain hemorrhage in contrast to what the CNN model predicts.... Dataset imbalance was employed in the research's second phase to totally eliminate all instances of false negatives. The CNN+ LSTM model outperforms CNN by achieving 100% accuracy, 95% F1-score, 95.54% precision, 100% sensitivity, and 100% specificity without ever making a mistaken prediction that puts the patient's life in jeopardy. As a result, the recommended model may accurately and quickly identify a brain hemorrhage and help save lives by predicting with a 100% accuracy rate. Image segmentation will be considered in the future as the color separation through segmentation will elucidate the sites of internal bleeding in CT scans in greater detail.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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