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Original Article

A Novel Weighted Average 2D-CNN Ensemble for Intracranial Hemorrhage CT Image Classification

Santwana Gudadhe[1*], Anuradha Thakare[1]

[1]*Department of Computer Science & Engineering (AI&ML), Pimpri Chinchwad College of Engineering, Pune, India.*

[*]*Corresponding Author : s.santwana20@gmail.com*

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Abstract - *Rapid and precise diagnosis and treatment of brain hemorrhage is of the highest importance because of the serious danger it presents to human life. Depending on where and how the bleeding is occurring, several distinct kinds of brain hemorrhage can be distinguished. Five subtypes of hemorrhage are covered in the primary division: subdural, epidural, intraventricular, intraparenchymal, and subarachnoid. Intracranial hemorrhage Computed Tomography (CT) image classification using the proposed weighted average 2D-Convolution neural network model has been proposed for intracranial hemorrhage subtype CT image classification. Intracranial hemorrhage subtypes, Intracranial Hemorrhage (ICH), Subdural Hemorrhage (SAH), Epidural Hemorrhage (EDH), and normal subtypes are outlined in this article. Three separate neural network models using two-dimensional convolution were evaluated for the purpose of bleeding subtype classification. Finally, a new ensemble model for a weighted average 2D convolution neural network has been designed. The suggested ensemble model can distinguish between 4 types of hemorrhage. Applying the proposed model to the test dataset reveals a maximum accuracy of 95.86%. In terms of classification, the suggested model can achieve a respectable degree of precision*.

Keywords - *Intracranial hemorrhage, Convolution neural network, Weighted average 2D-convolution neural network ensemble model, Classification.*

1. Introduction

In the medical field, an Intracranial Hemorrhage (ICH) refers to a specific kind of bleeding that takes place within the skull (cranium). In general, hypotension, trauma, weak blood vessels, and substance addiction are the factors that cause such a medical problem as this. Due to the fact that it has a significant probability of developing into a secondary brain injury, which can result in a serious condition if it is not treated immediately, it is regarded as a clinically serious condition [1, 2, 3]. ICH, or intracerebral hemorrhage, is a life-threatening condition that necessitates immediate medical treatment and extensive interventions at the appropriate moment. Roughly 10% of stroke fatalities are attributed to intracranial hemorrhage. Diagnosing the specific form of acute ICH is the first step in providing effective treatment. Subarachnoid Hemorrhage (SAH), Intraventricular Hemorrhage (IVH), Intraparenchymal Hemorrhage (IPH), Subdural Hemorrhage (SDH), and Epidural Hemorrhage (EDH) are some of the several kinds of cerebral hemorrhage. Subdural hemorrhage generally occurs as a result of the rupture of veins that are bridging the dura and the arachnoid membrane [4]. A subarachnoid hemorrhage is a type of brain hemorrhage that happens when blood clots in the space beneath the skull cap, usually because of bleeding in the cerebral artery. Any bleeding that happens within a brain ventricle is known as an intraventricular hemorrhage. A cerebral hemorrhage can happen anywhere in the brain's neural tissue (intraparenchymal hemorrhage) or between the dura mater and the skull (epidural hemorrhage). Medical imaging interpretation tasks have recently seen the development of numerous AI algorithms based on deep learning that achieve accuracy levels comparable to those of specialist physicians. Among the several deep neural network models utilized by the medical imaging community, Convolutional Neural Networks (CNNs) rank high [5, 6]. A breakthrough in ICH condition identification has been made possible by CNN's advancements and its capacity to demonstrate superior performance in classification tasks. Medical professionals can learn more about the site, size, and age of a cerebral hemorrhage by accurately classifying CT scans of the bleeding. The ideal treatment plan, which can involve medication, surgery, or other procedures, is decided upon with this information. In addition, the risk of impairment or mortality in patients with cerebral hemorrhage can be better predicted using the categorization of CT images taken during the procedure. Doctors and other medical professionals can use this data to assist patients and their families better. Many medical imaging researchers have applied AI and deep learning [7, 8]. Brain disease diagnosis is best done with a Computerized

Tomography (CT) scan since it has superior spatial resolution. Visualizing brain regions makes them more responsive to brain hemorrhage, making it better for brain disease diagnosis. Since brain hemorrhage might be mistaken as calcifications or stripping artifacts, radiologists find it difficult to diagnose ICH from CT scans. Even exquisite hemorrhage might vary in size, shape, and location despite having the same ICH subtype.

Recent research studies have placed a greater emphasis on the application of deep learning techniques for classification in the field of intracranial hemorrhage. Among the several deep neural networks, the Convolution Neural Network (CNN) has proven to be the most promising. It is possible to improve the accuracy of classification by taking into consideration the strength of the CNN model. The ensemble model is a combination of several separate models, and by combining the strengths of each model, it is possible to improve the accuracy of classification performance. The ensemble is able to assist in overcoming the shortcomings of any one of the models by assigning them a minimal weightage and by demonstrating that the model with the greater strength is the one that should be given a higher weightage during the prediction task. This will help the practitioner to make more accurate decisions during treatment.

This study aims to find and categorize ICH and its variants using a deep learning model called a Weighted Average 2D-CNN (WA2D-CNN) ensemble. The normal subtype is Intracranial Hemorrhage (ICH), Subdural Hemorrhage (SAH), and Epidural Hemorrhage (EDH). Presented below are the primary benefits of the proposed work:

- Intracranial hemorrhage CT image subtype classification using the proposed WA2D-CNN ensemble model is proposed.
- Different combinations of three 2D-CNN models are utilized to perform the subtype classification.
- Finally, the performance analysis of the proposed model is evaluated with precision, accuracy, sensitivity and F1-score.

Section 1 provides a concise overview of the proposed work and highlights the significant contributions to the associated topic. Section 2 provides a comprehensive analysis of the current research on the subject. Section 3 discusses the technique, which includes the database and proposed novel WA2D-CNN ensemble model. Section 4 discusses the results obtained for three different 2D-CNN models and the proposed model. Section 5 discusses the findings and observations obtained in the current study. Finally, the research study is concluded in the conclusion section.

2. Literature Survey

The use of deep learning techniques for image classification and segmentation has garnered an increasing amount of interest among researchers over the past several years. Since their dependability and effectiveness have contributed to their rise in popularity, Convolutional Neural Networks (CNNs) have emerged as important components in the field of medical diagnosis support. Past research has explored many facets of applying deep learning approaches to classify CT images of cerebral bleeding. The medical imaging community relies on Convolutional Neural Networks (CNNs) more than any other kind of deep neural network. A novel deep-learning technique for Artificial Neural Networks (ANNs) was put through its paces in the study [9] in order to detect and categorize ICH by making use of minimum datasets. The goal of the investigation was to see how well the technique could perform. It was claimed that the algorithm had a 91.7% accuracy rate when it came to accurate diagnosis of Subarachnoid Hemorrhage (SAH). A comparison was made between the diagnostic performance of the innovative deep-learning algorithm and that of previous techniques. This evaluation was carried out without the use of CNN.

To identify brain hemorrhage in CT scans, deep learning techniques and CNNs were applied in the study [10]. The ability to classify images as either haemorrhaging or non-haemorrhaging was assessed using two pre-trained CNNs (VGG16 and VGG19). Comparing the pre-trained VGG16 model against the VGG19 model, the former demonstrated remarkable accuracy. Among all the reference studies, the VGG16 model had the best accuracy, coming in at 99.10%. In [11], the authors suggested a simple framework for classifying brain hemorrhage situations in CT images using a popular, pre-trained deep Convolutional Neural Network (CNN) model. The relevant model was AlexNet. A pre-processing pipeline was introduced with the express aim of removing irrelevant brain regions that would otherwise make hemorrhage detection more difficult. The author has explored the prospect of utilizing a tweaked AlexNet-SVM classifier for the categorization job. Principal Component Analysis (PCA) is a feature section approach that was used in the upgraded AlexNet-SVM classifier pipeline to select the most discriminant features for classification. Outperforming the competing frameworks, the tweaked AlexNet-SVM classifier has proven to be the most effective. For the purpose of detecting Intracranial Hypertension (ICH) in CT scans of the brain, it has achieved a specificity and sensitivity of 99.8%.

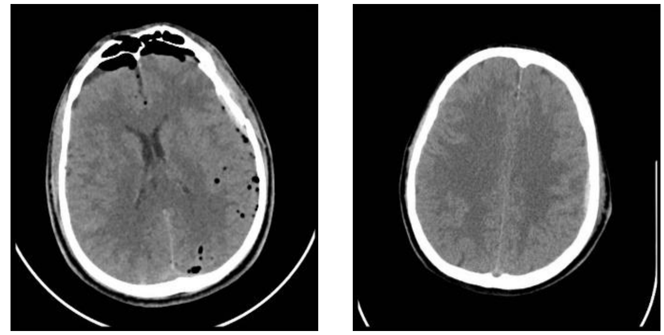
A higher relevance attribute selection technique, dMeans, is the foundation of the new pattern classification approach that was introduced in [12]. A key component of this approach is the ground-breaking Minimalist Machine Learning (MML) paradigm. This methodology is tested and compared to other classifiers, including the Multi-Layer Perceptron, Support Vector Machine, K-Nearest Neighbours, Naïve Bayes, AdaBoost, and Random Forest classifiers in order to carry out the task of classifying Computed Tomography (CT) brain images. A variety of convolutional neural network models, such as InceptionV3, VGG19, VGG16, ResNet152, and ResNet150, were utilized in the experiment for brain hemorrhage CT image categorization in [13]. Within the framework of the classification, a lightweight architectural model was presented. The proposed model has attained a higher level of accuracy compared to existing CNN models that have been pretrained. For the purpose of categorizing the five different forms of cerebral hemorrhage, a number of deep convolutional neural networks have been proposed in [14].

The SE-ResNeX50 and EfficientNet-B3 models serve as the foundation for the CNN model. An ICH diagnosis utilizing synergic deep learning and GrabCut-based segmentation was produced in a study [15] that used Deep Learning (DL) to diagnose the condition. The model was given the label GC-SDL. An improvement in image quality is possible as a result of the proposed method, which employs Gabor filtering for noise removal. Moreover, a segmentation technique that is based on GrabCut is utilized in order to detect the sick regions in the image successfully. Last but not least, the SoftMax (SM) layer is utilized as a classifier once the SDL model has been utilized to carry out the process of feature extraction. It was determined from the results of the experiment that the proposed model has achieved a higher level of sensitivity, which is 94.01%. Intracranial hemorrhage CT image classification using a hybrid feature-based method was proposed in previous study. The maximum accuracy was achieved using random forest was 87.22%. Within the context of the classification of Intracranial Hemorrhage (ICH), the author of [17] proposed an efficient deep learning model. To strike a balance between speed and computing efficiency, the suggested model employs a multi-receptive field method in conjunction with depthwise separable convolutions. Model validation and training were done using the CQ500 and PhysioNet datasets, with the RSNA datasets serving as the basis.

3. Materials and Methods

3.1. Dataset

Intraventricular, intraparenchymal, subarachnoid, epidural, and subdural cerebral hemorrhage were among the 36 patient scans included in the dataset retrieved from Kaggle [18,19]. There are around 30 slices with a thickness of 5 mm in each CT scan that is performed on a patient. To determine the type of hemorrhage or fracture that occurred, two radiologists examined each slice of the non-contrast CT scan. The radiologists in each slice also marked the ICH regions, and they saved the areas as white areas in a black and white 650x650 image (.jpg format). Both the brain and the bone CT slices also included 650x650 grayscale pictures stored in jpg format. Some examples of the images in the collection are displayed in Figure 1.



Hemorrhage Scan Normal Scan

Fig. 1 Sample images from the dataset

3.2. Proposed Novel WA2D-CNN Ensemble Model

To categorize CT images of cerebral hemorrhage, the suggested WA2D-CNN ensemble model is shown in Figure 2. Separate components make up the proposed methodology. Utilizing three 2D-CNN models for feature extraction and the proposed model for additional classification of CT images including cerebral bleeding. When it comes to ICH classification, Convolution neural network models are top-notch. Taking into account CNN models and ensemble models of CNN can boost classification accuracy by integrating the best features of multiple models and making up for their shortcomings. The ensemble model is able to make the most of each model's strengths while reducing their limitations because it combines each model.

This paper proposes the WA2D-CNN ensemble model, which uses weights to enhance the 2D-CNN ensemble model's performance. Following trials with three separate 2D-CNN models, the suggested WA2D-CNN ensemble model has the highest classification accuracy.

The proposed WA2D-CNN ensemble model for classifying CT images of intracranial hemorrhage includes the following:

1. Input image data
2. Feature Space Extraction Using Three Different Models:
   - Classification Using First CNN Model
   - Classification Using Second CNN Model
   - Classification Using Third CNN Model
   - Classification using an Ensemble of Three Different Models.
3. Comparison of Ensemble Model with Individual Models.

Table 1. Baseline characteristic of the dataset

Hemorrhage Subtype	No. of Images
Intracranial hemorrhage	412
Subdural hemorrhage	131
Epidural hemorrhage	526
Normal	1441
Epidural	182

3.2.1. Input Image Data

A total of 2510 images were considered including hemorrhage and normal class. The dataset is split into 80% training and 20% testing data. The dataset includes 5 different classes. As per the patient demographics file, some classes were overlapped, and one CT scan with two labels in that case, one of the labels was assigned to the scan to handle this issue.

Finally, 4 classes were considered: Intracranial hemorrhage (ICH) with 412 images, Subdural Hemorrhage (SAH) with 131 images, Epidural Hemorrhage (EDH) with 526 images, and normal subtype with 1441 images.

The dataset was highly imbalanced. To handle the data unbalancing, equal weights were assigned to each class. During preprocessing images were resized to 256x256 size to reduce the computation time. Data split into 80 percent training and 20 percent testing for experimentation. Table 1 shows the Baseline characteristics of the datasets provided in the dataset [18].

3.3. Feature Extraction Using Three Different Models

Three different 2D Convolution Neural Network (CNN) models were used to get ensemble based 2D CNN models for classifying the intracranial hemorrhage CT images. The first 2D CNN model with 12 layered architecture, the second 2D CNN model with 11 layered architecture and the third model with 9 layered architectures are considered to form ensemble-based 2D CNN models.

The first model is a 12-layered 2D-convolution neural network in which 6 Convolution layers, 3 max-pooling layers, and 3 dropout layers were added. In the second model, the 10-layered 2D Convolution Neural Network (CNN) architecture formed with 7 convolution layers and 3 max pooling layers were considered.

Finally, the third model is designed with 9 layers, of which three convolution layers, three max pooling layers, and dropout layers were considered.

Three distinct feature spaces are derived from these three models and then combined to form an optimal feature space. Here, a grid search combination was used to choose the best-optimized categorization model by assigning three weights –weight 1, weight 2, and weight 3 to three separate models.

In order to produce more accurate predictions, an ensemble model combines the output of multiple models. An advantage of using an ensemble over individual models is that, in the event that one of them makes a bad prediction, the other models can step in and make up for it. Figure 3 shows the three 2D-CNN models that make up the WA2D-CNN ensemble model.

3.4. Classification Through the Utilization of an Ensemble of Three Distinct Models

The classification task is performed using three different 2D-CNN models. Each CNN model was individually experimented for the classification task and accuracy was observed. Further weighted sum 2D-CNN ensemble model is experimented with and compared with each 2D-CNN model.

Finally, performance is observed for the proposed WA2D-CNN ensemble model. Performance evaluation is observed for Intracranial Hemorrhage (ICH), Subdural Hemorrhage (SAH), Epidural Hemorrhage (EDH), and normal subtypes.

3.5. Proposed Ensemble Model vs Individual Model Comparison

Finally, the performance of the proposed model was observed for each different 2D-CNN model, which is used to build the proposed model discussed in the result section below.

4. Results and Discussion

This part delves into the outcomes of the experiments. It is possible to gauge the model's efficacy by looking at its F1 score, sensitivity, accuracy, and precision [16, 20]. Both Section 4.2 and Section 4.1 cover the results of the proposed model, with the latter delving into the assessment measures used to assess the former.

4.1. Evaluation Metrics

4.1.1. Precision

The accuracy of a class's pattern predictions is defined as the proportion of correct predictions. Equation (1) determines the level of accuracy. Where FN, FP, TN, and TP stand for false negatives, false positives, and true negatives, respectively.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

4.1.2. Sensitivity

Sensitivity measures % of correctly classified patterns from positive ones. The formula for calculating sensitivity is Equation (2).

$$Sensitivity = \frac{TP}{TP+TN} \tag{2}$$

4.1.3. Accuracy

The ratio of accurate predictions to total occurrences is used to quantify classification accuracy. Using Equation (3), accuracy is determined.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{3}$$

4.1.4. F1-Score

The harmonic mean of sensitivity and precision is the F1-score. Using Equation (4), calculate F1-score.

$$F1-Score = \frac{2*(Precision*Sensitivity)}{Precision+Sensitivity} \tag{4}$$

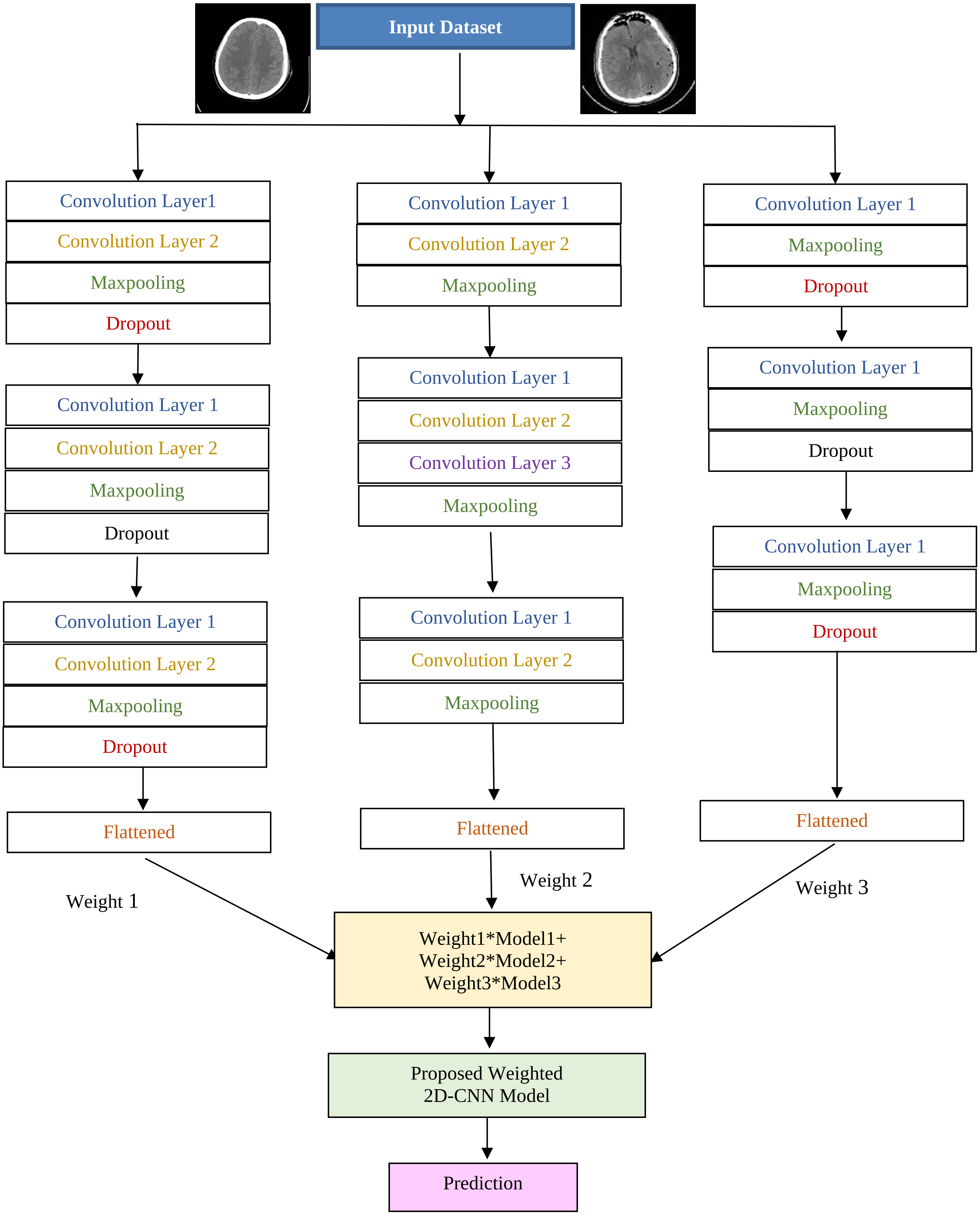


Fig. 2 Proposed WA2D-CNN architecture

4.2. Result Analysis

This subsection discusses the results obtained for each 2D-CNN model, followed by the proposed WA2D-CNN ensemble model.

4.2.1. Model 1: Classification Using 2D CNN Model 1

Six convolution layers, three max pooling layers, and three dropout layers were considered for the initial two-dimensional Convolutional Neural Network (CNN) model, which had twelve layers. Performance is evaluated for normal, Intracranial Hemorrhage (ICH), Subdural Hemorrhage (SAH), and Epidural Hemorrhage (EDH) subtypes. For every subtype categorization, sensitivity, F1-score, and precision were determined. Model 1 achieved a testing accuracy of 92.44%. Results for the initial 2D CNN model are displayed in Table 2. With the addition of three dropout layers to address the overfitting problem, the accuracy and overall performance of the first 2D CNN model with 12 layers improved.

4.2.2. Model 2: Classification Using 2D-CNN Model 2

In the second model, the 10-layered 2D Convolution Neural Network (CNN) architecture formed with 7 convolution layers, 3 max pooling layers was considered. Classification accuracy for Intracranial hemorrhage (ICH), Subdural hemorrhage (SAH), Epidural hemorrhage (EAH), and normal subtype categories. Precision, Sensitivity, and F1-score were calculated for each subtype classification.

The maximum testing accuracy observed was 89.86 % using the second model. Table 3 shows the result obtained for the second 2D CNN model. As compared to the first model, the second model was overfitted as no dropout layer was considered. In the case of the first model, after each convolution layer, a dropout layer was added. Due to overfitting issues, the model did not perform well as compared to the first model.

4.2.3. Model 3: Classification Using 2D-CNN Model 3

The third model takes into account three max pooling layers, three dropout layers, and three convolution layers among its nine layers. In this model, after convolution, dropout was added. In all individual models this model performs well. Validity of classification for subtypes of normal, intracranial, subdural, and epidural hemorrhages for every subtype categorization, sensitivity, F1-score, and precision was determined. For model 3, the obtained testing accuracy was 93.24%. Table 4 displays the outcome of the third 2D Convolutional Neural Network model.

4.2.4. Classification Using the Proposed Ensemble of Three Different Models

Combining three feature spaces derived from three 2D-CNN models allows for the construction of classification using an ensemble of three distinct models. The WA2D-CNN ensemble model is constructed after weights are assigned to each 2D-CNN model. The first 2D Convolutional Neural Network (CNN) weighted sum ensemble model was experimented with. By adjusting the model weights from 0.0 to 0.5. The proposed WA2D-CNN ensemble models use grid search to get the optimal weight combination. 0.2, 0.1, and 0.4, which were the ideal weights for the proposed model to perform efficiently. The proposed weighted sum model has achieved a higher accuracy of 94.21%, and the proposed WA2D-CNN model has achieved a maximum testing accuracy is 94.86%. Table 5 displays the outcome of the WA2D-CNN ensemble model that was suggested.

Table 2. Result analysis for the first 2D CNN model

Hemorrhage Subtype	Precision (%)	Sensitivity (%)	F1-Score (%)
Intracranial Hemorrhage (ICH)	86.67	85.85	86.26
Subdural Hemorrhage (SAH)	98.26	89.16	93.67
Epidural Hemorrhage (EAH)	92.28	95.82	94.02
Normal	100	92.59	96.15

Table 3. Result analysis for the second 2D CNN model

Hemorrhage Subtype	Precision	Sensitivity	F1-Score
Intracranial Hemorrhage (ICH)	90.91	75.47	82.47
Subdural Hemorrhage (SAH)	87.06	89.16	88.10
Epidural Hemorrhage (EAH)	90.40	95.12	92.70
Normal	89.29	92.59	90.91

Table 4. Result analysis for the third 2D CNN model

Hemorrhage Subtype	Precision	Sensitivity	F1-Score
Intracranial Hemorrhage (ICH)	87.04	88.68	87.85
Subdural Hemorrhage (SAH)	94.05	95.18	94.61
Epidural Hemorrhage (EAH)	95.09	94.43	94.76
Normal	96.15	92.59	94.34

Table 5. Result analysis for WA2D-CNN ensemble model

Hemorrhage Subtype	Precision	Sensitivity	F1-Score
Intracranial Hemorrhage (ICH)	89.52	88.68	89.10
Subdural Hemorrhage (SAH)	96.34	95.18	95.76
Epidural Hemorrhage (EAH)	95.17	96.17	95.67
Normal	96.15	92.59	94.54

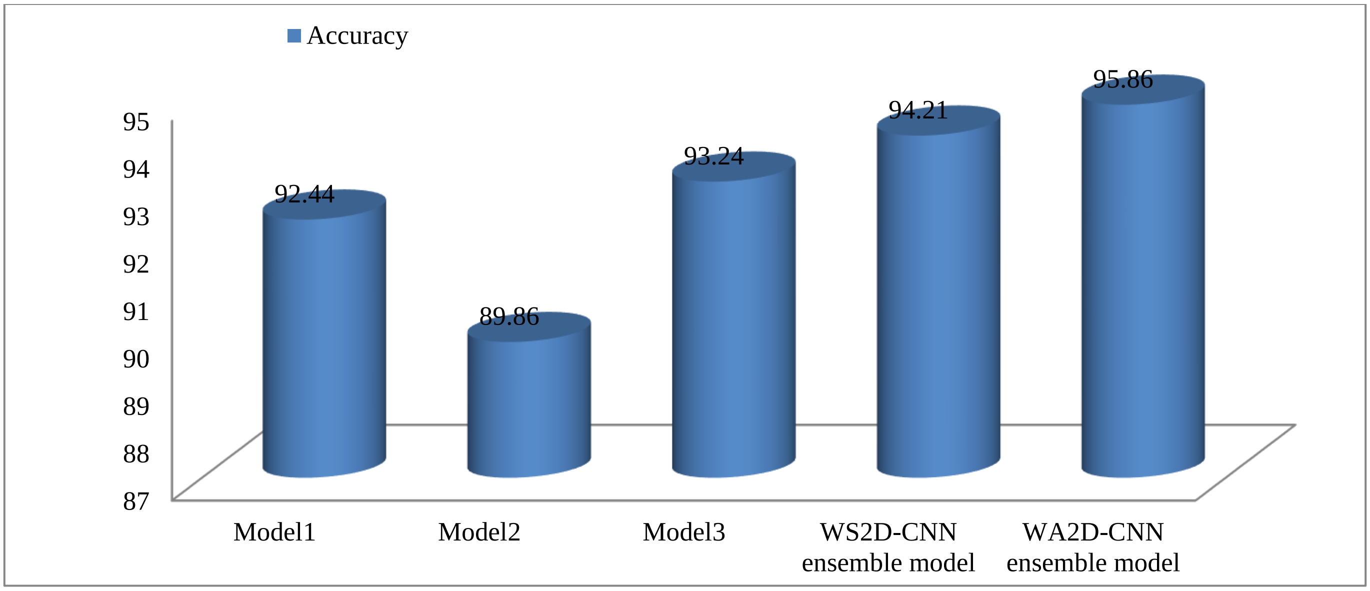
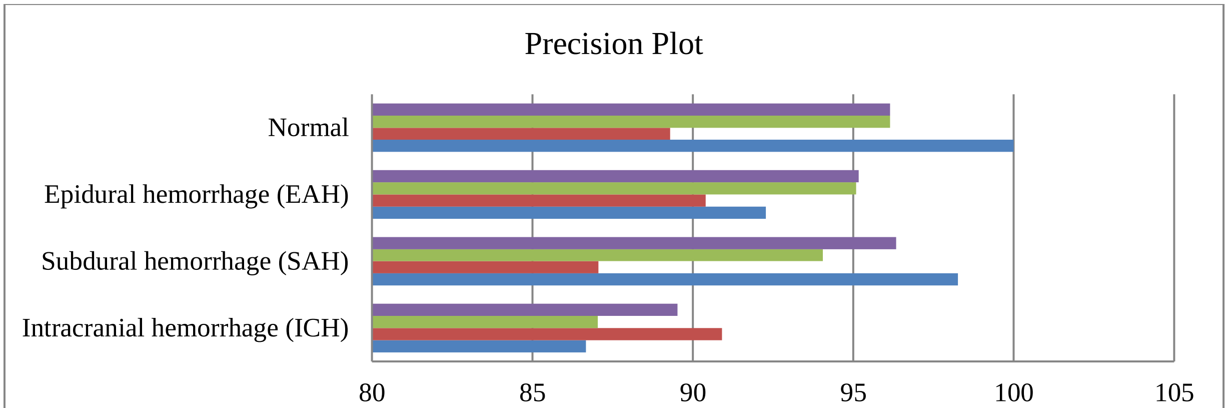


Fig. 4 Comparative analysis of the proposed model with other experimented models



	Intracranial hemorrhage (ICH)	Subdural hemorrhage (SAH)	Epidural hemorrhage (EAH)	Normal
Proposed Model	89.52	96.34	95.17	96.15
Model3	87.04	94.05	95.09	96.15
Model2	90.91	87.06	90.4	89.29
Model1	86.67	98.26	92.28	100

Fig. 5 Comparative analysis of the precision plot of the proposed model with other models

Table 6. Comparison of research studies for intracranial haemorrhage CT image classification

Ref. No.	Technique Used/Algorithm	Performance Measure
[9]	Deep learning -CNN	AUC- 90.3, Sensitivity- 82.5, Specificity – 84.1
[10]	VGG16, VGG19	Accuracy-99.10
[11]	Alex-Net -SVM	Accuracy-99.86
[12]	Minimalist Machine learning Algorithm	Accuracy 86.5, Specificity – 91.6
[13]	VGG16	Accuracy - 96
[14]	VGG16, VGG19, ResNet150, 152, Inception V3	Accuracy- 96.67, Sensitivity-97.08, Specificity- 96.25
[15]	GC-SDL	Sensitivity-94.01, Specificity-97.1
Previous	GLCM-RF	Accuracy -87.22
[17]	Efficient Deep Learning Model	AUROC-95.2

Each 2D-CNN model is experimented and classification accuracy is obtained for all three 2D-CNN models. Model 1 obtained a maximum accuracy of 92.44%. Model 2 has achieved a maximum accuracy of 89.86 %, and Model 3 has achieved a maximum accuracy of 93.24 %. Figure 4 shows the comparative analysis of the proposed model's accuracy with other experimented models. Figure 5 shows the precision plot for all models.

As compared to model 1 and model 2, model 3 is simple and less complex. Also, a dropout layer is added after each convolution block. Due to the dropout layer, model 3 is not overfitted. In the case of model 2, no dropout is added. Because of this, model 2 is overfitted and observed with less accuracy. To provide forecasts that are more accurate and resilient, ensemble models are a great option. Considering this idea proposed WA2D-CNN ensemble model using three 2D-CNN models is built. The proposed weighted sum 2D-CNN model is built and obtained 94.21% accuracy. Finally, the proposed WA2D-CNN ensemble model observed a maximum accuracy of 95.86 %.

4.2.5. Comparison of Proposed WA2D-CNN Model with State-of-Art

Table 6 provides a comparison of research studies for intracranial hemorrhage CT image classification. Research mainly focuses on binary classification and subtype classification of hemorrhage CT images. In [9] area under the curve obtained was 90.3%, sensitivity 82.5%, and specificity 84.1%. Using pretrained VGG16, VGG19 models obtained an accuracy was 99.10% reported in [10]. In [11] AlexNet-SVM classification model was experimented with in order to classify the hemorrhage CT images. Maximum accuracy obtained was 99.86%. For intracranial hemorrhage, CT image classification using a minimalist machine learning algorithm obtained an accuracy was 86.5% specificity was 91.6 [12]. Using the VGG16 model maximum accuracy reported was 96% in [13]. In research [14], pretrained models were utilized like VGG16, VGG19. The maximum sensitivity reported was 97.08, and specificity was 96.25%. Using the GC-SDL model, the sensitivity obtained was 94.01 was sensitivity was 97.7% reported in [15]. With the use of GLCM features and the Random Forest algorithm, the maximum accuracy reported was 87.22% in the previous study of this work. In [17], using an efficient deep learning model, AUROC reported was 95.2%. The proposed WA2D-CNN model has achieved a maximum accuracy of 95.86% with 96.34% precision for ICH, 96.43% precision for SAH, 91.74% precision for EAH and 97.18% precision for normal subtype.

5. Conclusion

The purpose of this study is to present a WA2D-CNN ensemble model for intracranial hemorrhage CT image subtype classification. Deep learning models can be thrown off by a number of factors, including random weight initialization, hyperparameter selection, and training data sets that are completely unpredictable. An ensemble model is a combination of multiple models that have been trained on different regions of the data with distinct hyperparameters. This helps to reduce the amount of uncertainty that is there. The proposed WA2D-CNN ensemble model is constructed using this fundamental concept.

Compared to all of the other models that were tested, the proposed model has the highest possible accuracy of 95.86%. A grid search is carried out in order to find the optimal combination of weights, and the results show that the optimal combination of weights for model 1, model 2, and model 3 are 0.2, 0.1, and 0.4, respectively. In the case of Intracranial Hemorrhage (ICH), Subdural Hemorrhage (SAH), Epidural Hemorrhage (EDH), and normal subtypes, the proposed model has achieved the maximum testing accuracy of 95.86%. A shortcoming of this work is that the dataset size is quite small. In the future, the scope may include image segmentation through the application of deep learning architecture. A decent approximation of the hemorrhage in the brain CT image will be achieved with the assistance of this.

Author Contributions

The contribution of the authors for this research are as follows: "Conceptualization, methodology, formal analysis, Santwana Gudadhe and Anuradha Thakare; investigation, writing—original draft preparation, Santwana Gudadhe; writing—review and editing, Santwana Gudadhe and Anuradha Thakare; visualization, Santwana Gudadhe; supervision, Anuradha Thakare; project administration, Anuradha Thakare.

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