Grenze International Journal of Engineering and Technology, June Issue

Deep learning for Intracranial Hemorrhage Detection

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***Abstract*— A possibly fatal medical condition with apoor prognosis is intracranial hemorrhage (ICH). Inpreviously published work, a more traditionalmethodology was applied, consisting of multiple stages of alignment, picture analysis, image rectification, manual image segmentation, and classification. For the classification of ICH sub types,we built a convolutional neural network based on thetransfer learning model. DenseNet121, Xception, and CNNs were assessed using a broad variety of evaluation criteria to ensure that the model producesexcellent results and is accurate. The ultimate outputfor the identification and classification of ICH subtypes is generated using the Xception model.**

***Index Terms*— Intracranial Hemorrhage, CT images, CNN ,DenseNet121, Xception.**

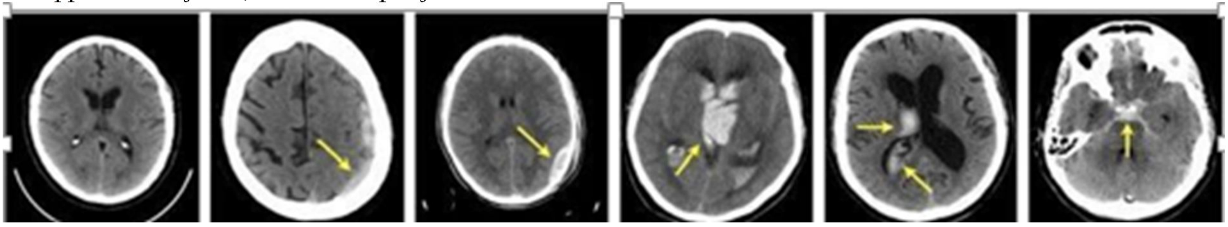
I. INTRODUCTION

The term "intracranial hemorrhage" (ICH) refers to bleeding that takes place inside the intracranial vault. Among the causes could include vascular anomalies, venous infarction, tumours, the effects of trauma, therapeutic anticoagulation, and cerebral aneurysm. A hemorrhage poses a serious concern no matter what the real reason is. Therefore, the effectiveness of the therapy procedure depends greatly on an accurate and prompt diagnosis. A non-contrast computed tomography (CT) scan of the affected area of the brain, along with the patient's medical history and physical exam, are used to determine whether the patient has ICH. The basic causes of ICH can be identified and localized bleeding is made possible by CT imaging. For medical purposes, hemorrhage detection should be very high. The diagnosis and treatment of ICH are complicated by a number of factors, including the procedure's urgency, the lengthy and involved decision-making process, the inexperience of new radiologists, and the fact that the majority of emergencies happen at night. As a result, a computer-aided diagnosis tool is desperately needed to help the specialist. However, for medical applications, automated hemorrhage detection should have a high enough accuracy level.

Several ICH subtypes can be recognised based on the anatomic location of the bleeding in the brain. While the epidural subtype (EDH) involves bleeding between the dura and the bone, subdural hemorrhage (SDH) refers to bleeding between the dura and the arachnoid. Both frequently follow from serious wounds. Bleeding within the parenchyma of the brain is known as intraparenchymal hemorrhage (IPH). Intraventricular hemorrhage (IVH) is a hemorrhage that occurs within the ventricular system. Last but not least, subarachnoid hemorrhage (SAH) is indicated by bleeding in the subarachnoid area. An aneurysm in the brain that has ruptured is one of the main causes of SAH. Due to similarities between the many ICH subtypes (such as SDH vs. EDH) and small distinctions between healthy and bleeding tissues, hemorrhage identification and categorization are difficult. The untrained.
spectator would hardly see these. We have seen a rise in interest in deep learning techniques for segmenting and classifying images among researchers in recent years. Due to their dependability and effectiveness, convolutional

Grenze ID: 01.GIJET.9.2.10

neural networks (CNNs) have grown in popularity and are now crucial components in the support of medical diagnoses.
CT scans are typically 3D structures made up of a stack of 2D slices. Operating on picture voxels is therefore feasible but may involve significant computing complexity. Processing slices separately or making simpler use of the 3D context are two ways to prevent the latter. The majority of the proposed deep learning methods for cerebral hemorrhage detection and classification have emerged in the previous three to four years. One-class detection relating to a single class of ICH found in a CT scan, multi-class classification differentiating ICH subtypes, or ICH pixel area detection within individual pictures are the subject of many research. Examples of pre-trained CNN models that have gained popularity include VGG, MobileNet, and ResNet-18.
Any age can be affected by an intracranial hemorrhage that causes a severe brain stroke, but individuals with high blood pressure are at an increased risk because the blood supply to the brainis restricted. In addition, intracranial hemorrhage (ICH), a brain disease that causes severe harm to people, is characterized by blood vessel damage and infected cells that gradually spread to the brainventricles. The data that is presently available suggests that there are approximately 795,000 strokes per year in the United States.



(a)Healthy brain (b) SDH (c) EDH (d) IPH (e) IVH (f) SAH

The usability of ML algorithms for image analysis, like neural networks, has been extended as a result of machine learning (ML) advancementsin object detection. Deep learning algorithms find significant elements and traits in big data bases without formal training. This suggests that they canreceive training from beginning to finish. A radiologist can anticipate and complete computed tomography (CT) scans using machine learning, even though they frequently reach for an expert.

II. RELATED WORK

The proposed study (Luong et al., 2020) managed a classification model to find brain hemorrhage using CT by employing deep learning, Hounsfield Unit (HU), and data clustering techniques. Deep learning approaches to image processing have become more popular because to the power of high-performance computing (HPC) technologies. In a study (Anupama et al., 2020), the identification of ICH was carried out utilising a combination of image segmentation, picture pre- processing, and the Gabor filtering approach to pre- process the noise. After that, the Grab Cut method was used for segmentation, and Synergic Deep Learning was used for feature extraction. CNN was used for feature extraction by (Sage and Badura; 2020) and numerous classifiers were used to identify various kinds of cerebral hemorrhage. The multiclass approach can occasionally be moderately incorrect due to the possibility that a single CT slice will reveal many ICH subtypes. The research (Burduja et al.; 2020) used convolutional and LSTM neural networks to detect cerebral hemorrhage in 3D CT images. The 2019 RSNA Brain CT Hemorrhage database was used in the paper. LSTM and CNN models simultaneously complete two classification tasks.
The researchers offer a redesigned u-net and curriculum learning technique throughout Paper (Wang et al.; 2020), which is based on a semi-attention-based multi-task model. The Radiological Society of North America (RSNA) ICH dataset comprises 36 ICH cases represented in the CT scans collected and recognised by Al Hilla Teaching Hospital in Iraq. An all- encompassing, end-to-end multitasking network for concurrent categorization and cerebral hemorrhage segmentation is proposed in the research (Guo et al., 2020).
For classification and segmentation, a comparable encoder is defined, and a contextual long-term storage module (ConvLSTM) makes it possible to capture contextual data. 1176 CT scans from three hospitals were used in the study. (Ginat; 2020) suggested using deep learning technology to diagnose acute hemorrhage on a non-contrast head CT. Researchers found that emergency hemorrhage identification accuracy was higher than hospital hemorrhage detection using Aidoc neural network software.
The outcomes of a deep learning DSS for identifying intracranial hemorrhage (ICH) were presented in detail in another study using the 3605 non- contrast head CT (Voter et al.; 2021). Age, gender, prior neurosurgery, the type of ICH, and the number of ICHs were all shown to be somewhat correlated with diagnostic accuracy, the

researchers found. The research (Imran et al., 2021) aimed to partition the site using an FCN architecture in order to locate hemorrhage and explain the characteristics of ICH observed. 36 of the 82 CT scans total, of which are of ICH patients. Following more research, the technologies RPN (Regional Proposal Network) and VGG architecture were implemented.
Three neural networks (VGG-19, DenseNet11, and Resnet-101) that were trained to detect intracranial hemorrhages were fed a set of 8898 ICH and regular CT images throughout the study (Wang et al.; 2021). The study's findings led to the development of a brand-new deep learning-based method for detecting intracranial hemorrhages and brain tumor’s (Kirithika et al., 2020). In order to improve the image resolution, the data is first pre-processed three times with bilateral filtering, contrast limitation, and skull stripping.
The goal of this study (Hebbar et al., 2020) was to use convolutional neural networks (CNNs) to build a comprehensive method for identifying brain hemorrhage in a CT picture. The ability of CNN models to identify the spatial and temporal relationships of a picture using a combination of several different filter types allowed the authors to assess them against other learning algorithms in computer vision tasks.
A convolutional neural network (CNN)-based Artificial Intelligence (AI) method to evaluate the effectiveness of ICH was mentioned by Rao et al. in 2021. The topic of intracranial acute hemorrhage and its subtypes is covered in detail in (Rane and Warhade; 2021). Hemorrhage pattern diagnosis uses transfer learning. The RSNA Brain CT Hemorrhage database on DICOM files and windowing strategies up till they are delivered to the system are included in the study. Without a window, the effectiveness plot shows a 0.944 rise over fewer epochs. The precision with windowing (0.956) result indicates a greater learning expectation.
Studies and methodologies that have been put out have a remarkable capacity to improve deep learning methods and achieve high accuracy in the classification of brain hemorrhage. The potential of deep-learning models to detect bleeding in the brain region was looked at in a study (Remedios et al.; 2020).

III. Design Technique

A. Modeling:

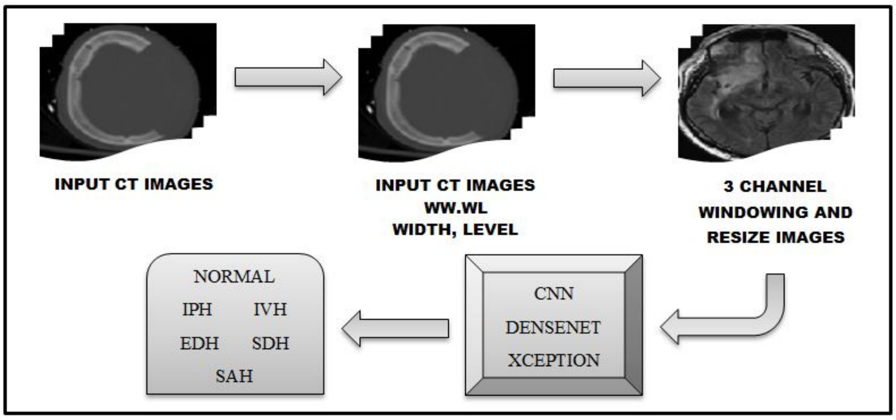
This stage makes use of the pre-processed data by applying three different models. The uniqueness of this research lies in the use of a pre-trained CNN model (Transfer Learning) to identify different types of intracranial bleeding. Pre-trained models like DenseNet121 and Xception are used to apply transfer learning to the generated data.

B. Pre- Trained Models (Transfer Learning):

The methods of transfer learning, which apply knowledge gained from one job to another, could be used to address the information gap revealed by the provided dataset. In the study paper (Wang et al., 2020), transfer learning is examined for picture segmentation on a smaller dataset. The researchers discovered that by adding more layers and creating a thick structure, more precise results can be achieved. ICH subtypes were predicted using transfer learning and an ensemble of four well-known CNN algorithms, with promising findings. (Anupama et al.; 2020). Studies on image categorization, visual classification, and object prediction have effectively used transfer learning, a type of deep learning. (Kirithika et al.; 2020). In a study that is similar to this one (Rane and Warhade; 2021), the bleeding types are identified using a transfer learning approach. According to a study, transfer learning appears to work well with medical image data.(Li et al.; 2020).
A 15 percent sample of the training data is used to verify the outcomes. The datasets are then put into image conversion after that. A Python library named "pydicom" was used in the research study by Wang et al. (2021) to extract the data from the DICOM files. Three different windowing methods are used with CT images. The images are windowed, resized to (128x128) using the "cv2" library, and saved in a separate folder. These images will be used as input for the training at the process step. The "ImageDataGenerator" package from Keras is utilised to resize the pictures. The data generator function gave the x column to the images column and the y column to the remaining Boolean columns, as well as the main path of the resized data file directory. The batch size was set to 32 and the image's goal size was (128x128). The Keras neural network library, which is based on the TensorFlow framework, was used in Python to build deep learning models.

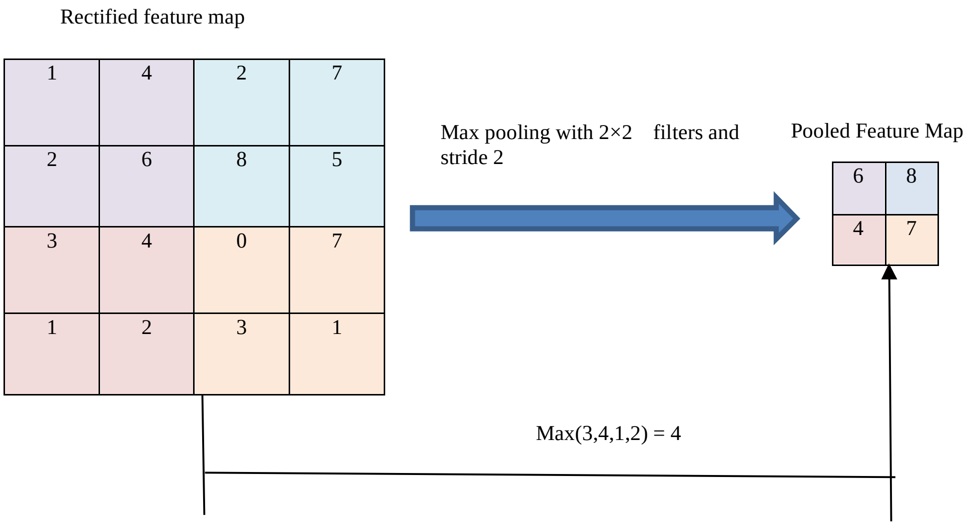
C. DenseNet121:

DenseNet has the benefit of improved feature rebuilding, which dramatically increases the design's efficiency. DenseNet has been gradually enhancing its accuracy while also enhancing its feature set without leading to over fitting or performance loss. DenseNet also has the ability to save a lot of time by increasing the number of features that can be reused in subsequent tasks. By increasing the number of features that can be reused in subsequent projects, DenseNet can also save a substantial amount of time.



D. Xception Model:

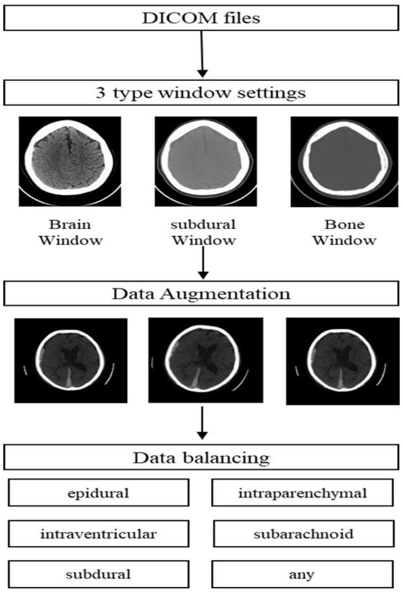
Xception model is a CNN architecture based on deeply convolutional layers. In the initial module, which generates cross-channel correlations and spatial interactions that can be completely disconnected within the CNN characteristic mapping, Xception is mentioned as the underlying assumption. This idea is thought of as a more sophisticated version of the Inception paradigm. The framework over extracting features is made up of 71 levels in the Xception architecture. There are 14 sections in the levels below it. With the exception of the first and last modules, these are deep layers of distinct layers of convolution that are layered linearly over the residual batch normalization. With the aid of a variety of sophisticated libraries, including Tensor Flow and Keras, this flexible element of design makes definition and change simpler.



IV. PERFORMANCE ANALYSIS OF ICH

For this research, a three-stage framework with a database layer, an application layer, and a presentation layer was chosen (Choudhury; 2020). The Kaggle API will be used in the initial phase of the research endeavor to collect all pertinent data. At the business logic layer, picture conversion, windowing, and resizing are also used to convert DICOM data to PNG format. Run an exploratory data analysis (EDA) after that to determine the data set's degree of distribution. Following that, the data collection is subjected to deep learning and transfer learning techniques. The presentation layer, which is the last level, uses Python libraries to visualise the existence or lack of various subtypes of intracranial hemorrhage.

Data extraction in line with model specifications is known as data transformation. The Kaggle API was used to retrieve the entire data set, which contains six distinct hemorrhage sub types. We must first unzip the folder because the data has been packed into a zip file before continuing. In order to save storage room, image conversion is used for DICOM pictures. Since PNG images are compressed without loss, they have better image clarity. 5000 randomly chosen images from the test dataset file and 50000 randomly selected images from the training data set file are used for modelling due to the restricted hardware available for implementation. Duplicate files have been deleted from the train and test data collections. The article (Burduja et al., 2020) (Hebbar et al., 2020) used methods for separating training and testing data to validate the model findings.



A 15 percent sample of the training data is used to verify the outcomes. The datasets are then put into image conversion after that. A Python library named "pydicom" was used in the research study by Wang et al. (2021) to extract the data from the DICOM files. Three different windowing methods are used with CT images. The images are windowed, resized to (128x128) using the "cv2" library, and saved in a separate folder. These images will be used as input for the training at the process step. The "ImageDataGenerator" package from Keras is utilised to resize the pictures. The data generator function gave the x column to the images column and the y column to the remaining Boolean columns, as well as the main path of the resized data file directory. The batch size was set to 32 and the image's goal size was (128x128). The Keras neural network library, which is based on the TensorFlow framework, was used in Python to build deep learning models.

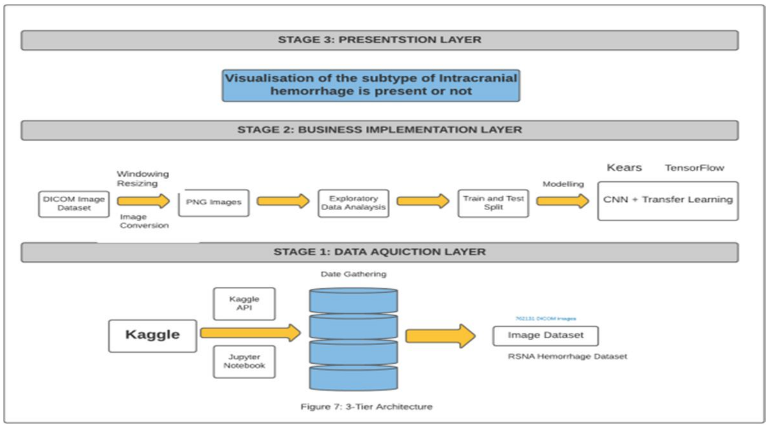


Fig: design architecture for the proposedresearch

V. Results and Discussion

There are numerous methods for calculating any classification or forecast model's success rate. Based on the data in the confusion matrix, the evaluation methods are employed. The real and predicted window levels and widths were calculated using a confusion matrix by (Viriyavisuthisakul et al.; n.d.). Data from the uncertainty matrix is used to evaluate the effectiveness of our devised strategy. In the confusion matrix, true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are all represented.

A. Metrics obtained from confusion matrix:

- A model's accuracy is determined by adding up both the total number of instances that are forecasted and the general number of instances that are correctly predicted. This demonstrates the effectiveness of the strategy. In the study, the model's exactness and precision were assessed. (Burduja et al.; 2020) Ho and Kim (2020) and Ginat (2021) (Guo et al.; 2020).
- Accuracy assesses the degree to which images with and without hemorrhage correspond to real bleeding.

B. Actual vs Predicted analysis:

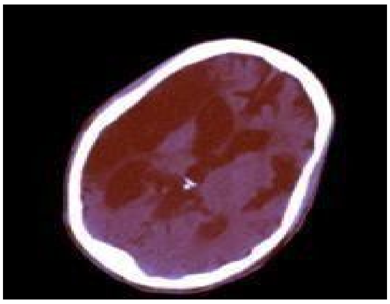


Fig: Actual analysis

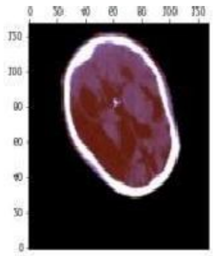


Fig: Predicted analysis

The above predictive image demonstrates how well themodel performs in detecting the subarachnoidhemorrhage on a reduced probability. The subtype of intracranial hemorrhage with the lowest chance of failure can be found using the Xception model.

- accuracy:

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \cdot 100\%, \qquad (1)$$

- sensitivity (recall, true positive rate):

$$TPR = \frac{TP}{TP + FN} 100\%, \qquad (2)$$

- specificity (true negative rate):

$$TNR = \frac{TN}{TN + FP} 100\%, \qquad (3)$$

- F1 score (Dice index):

$$F1 = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} 100\%, \qquad (4)$$

where *TP*, *TN*, *FP*, and *FN* denote the number of true positive, true negative, false positive, and false negative classifications, respectively.

ICH Subtype	Feature-Extraction Branch	ACC (%)	TPR (%)	TNR (%)	F1 (%)
Subdural (SDH)	Branch #1	88.7	87.6	89.9	88.9
	Branch #2	86.9	86.3	87.6	87.2
Epidural (EDH)	Branch #1	58.6	56.2	61.0	57.5
	Branch #2	66.4	47.7	85.1	58.6
Intraparenchymal (IPH)	Branch #1	92.4	91.7	93.1	92.2
	Branch #2	92.1	91.7	92.5	92.0
Intraventricular (IVH)	Branch #1	95.5	94.9	96.0	95.1
	Branch #2	95.7	96.0	95.4	95.6
Subarachnoid (SAH)	Branch #1	88.0	87.3	88.8	87.8
	Branch #2	88.2	91.0	85.4	88.7

Summary of evaluation metrics obtained in Experiment #1 for individual ICH subtypes and ResNet models.

ICH subtype	Classifier	ACC (%)	TPR (%)	TNR (%)	F1 (%)
Subdural (SDH)	SVM	87.1	83.7	90.7	87.0
	RF	89.1	86.7	91.7	89.1
Epidural (EDH)	SVM	76.9	73.4	80.1	75.3
	RF	74.3	68.6	79.9	72.7
Intraparenchymal (IPH)	SVM	91.9	93.1	90.7	91.7
	RF	93.3	93.9	92.6	93.1
Intraventricular (IVH)	SVM	96.0	97.1	94.9	95.9
	RF	96.7	96.7	96.7	96.6
Subarachnoid (SAH)	SVM	86.8	86.1	87.6	87.6
	RF	89.7	90.0	89.4	89.9

Summary of evaluation metrics obtained in Experiment #2 for individual ICH subtypesand classifiers

C. Actual and Loss variation:

The effectiveness of the learning curve of a full range picture with and without windowing was assessed by (Rane and Warhade; 2021) using training and validationaccuracy plots. Two deep learning models werecompared in the research (Hebbar et al., 2020) using their testing and training accuracy for each model used in this study, as well as loss variation.

Also, since the curves are placed farther apart from oneanother than from another, there is a slight decrease in overfitting in the CNN model. The accuracy of trainingand validation was used in the article (Luong et al., 2020) to balance the sensitivity and specificity values. The precision of the model will rise as the model's training-time accuracy keeps getting better. But there will be a substantial loss in sensitivity. The loss for boththe training and validation datasets diminishes as the training dataset's number of iterations rises. Despite thefact that there are few differences in the validation dataset's accuracy.

Figures 10, 11, and 12 show the overfitting of each model with respect to curve fit. Also, as the curves are placed farther apart from one another than from another, there is a slight reduction in overfitting in the CNN model. The accuracy of training and validation was used in the publication (Luong et al., 2020) to balance the sensitivity and specificity values. The model's specificity will rise if the model's training-time accuracy keeps getting better. But there will be a sharp drop in sensitivity. Utilising CNN has a smaller impact on training and validation accuracy, as well as a smaller impact on both training and validation loss. The loss for both the training and validation datasets diminishes as the training dataset's number of iterations rises.

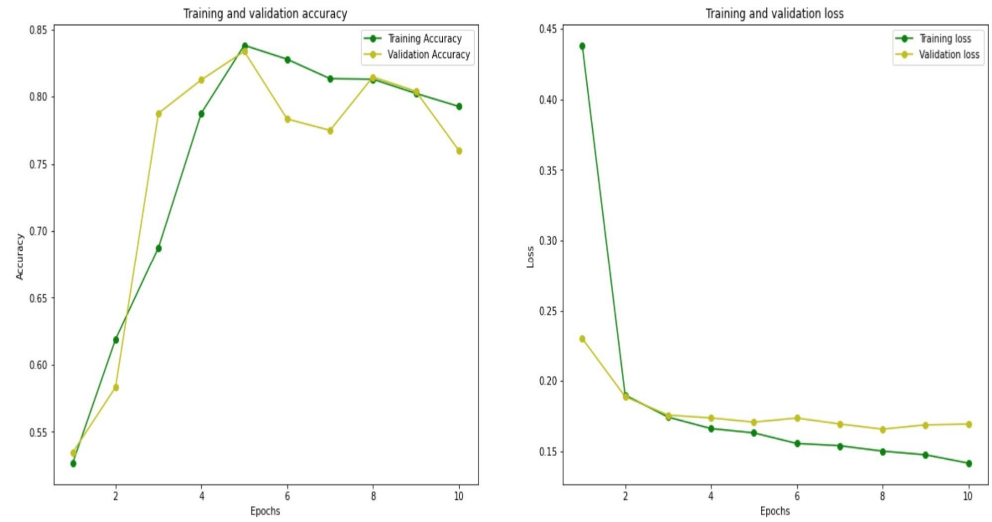


Figure 10: CNN Accuracy and Loss Graph

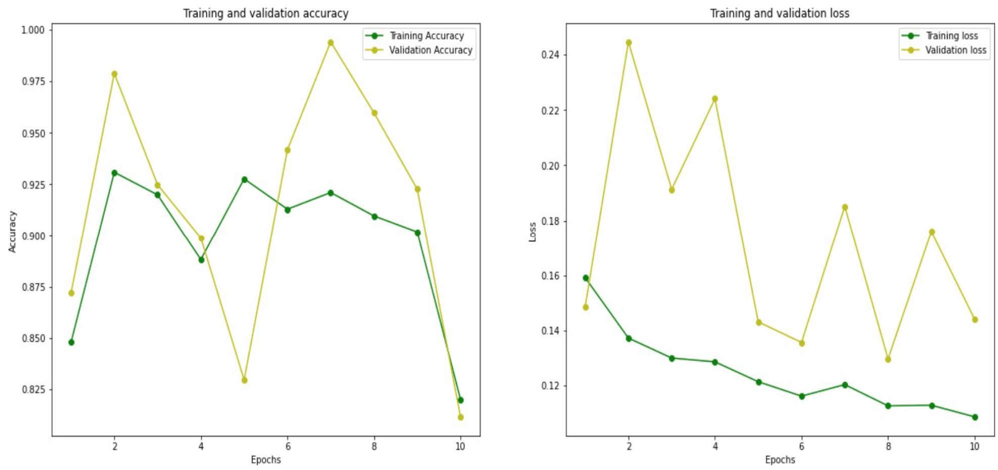


Figure 11: DenseNet121 Accuracy and Loss Graph

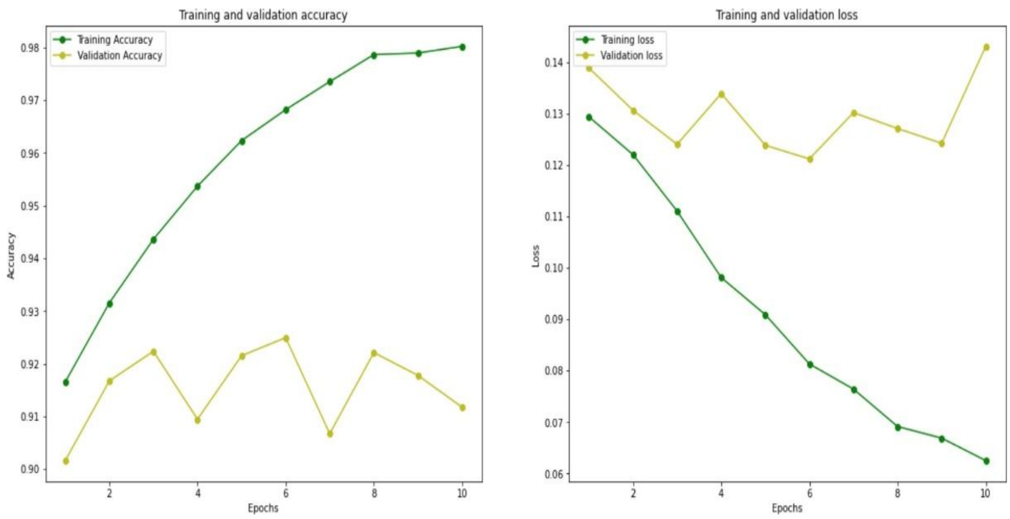
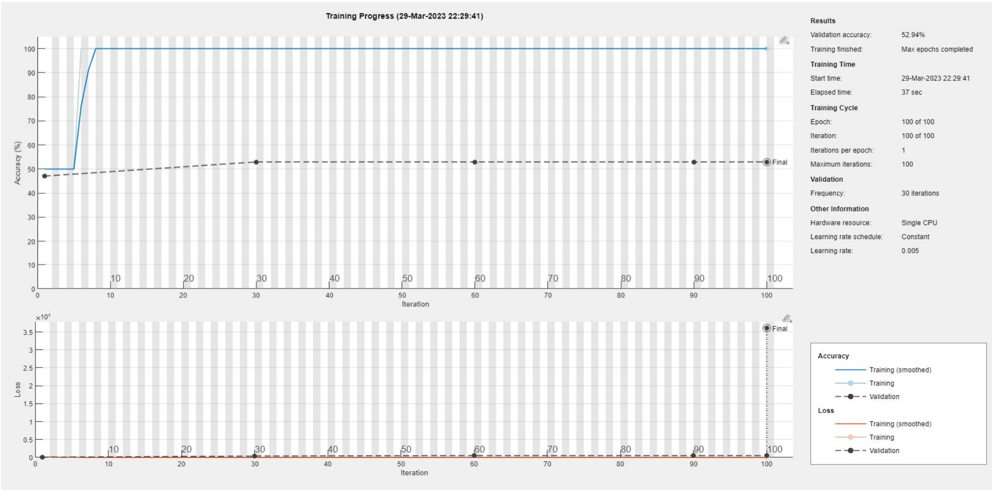


Figure 12: Xception Accuracy and Loss Graph



Output using sample of images

	50	10	9	5	16	8
	12	57	17	2	6	4
	9	13	26	12	26	12
	9	9	21	34	11	14
	20	12	17	10	21	18
	11	17	22	4	14	30
	1	2	3	4	5	6
	Predicted case					

6. classes confusion matrix

VI. Conclusion

In this paper we addressed the discovery of colorful intracranial hemorrhage types by employing double- branch deep point birth and machine literacy classifiers. The results justify the idea of searching for applicable features in different representations of the data(regularized image in multiple intensity windows and 3D spatial environment) and their consecution for bracket using arbitrary timber. The system offers the loftiest discovery effectiveness in intra ventricular and intra parenchymal hemorrhage.

We created a framework that performs single frame CT image analysis better than a radiologist and can recognise and categorise ICH as intraparenchymal, intraventricular, subarachnoid, subdural, or epidural.On the RSNA dataset (Kaggle; 2021), a sizable labelleddataset made up of 762131 CT scans in DICOM format,our model was trained. The CT images are converted using windowing to 16-bit DICOM images with vectorsof floating-point numbers that are standardised in the (0, 1) range.

Only 55000 scaled PNG images in the (128x128) dimensional format are used in this research. The approach we suggested enhances ICH detection and classification with an accuracy of 91% and can assist doctors in the analysis of head CT images. We used theCNN and transfer learning model (Xception model andDenseNet121). With a lower chance of failure, the Xception model can recognise the different subtypes ofintracranial hemorrhage. When used on a large image collection, the model has a very high chance of increasing accuracy for future research.

Model	Accuracy	Precision	F1-Score	Recall
CNN	86	0.89	0.92	0.96
DenseNet	90	0.95	0.94	0.94
Xception	91	0.95	0.95	0.95

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