International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 07 | July - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

BrainHemorrhage Detection Using AI

[1] Dr. M Prasad , [2] Fiza Tabassum J M

[1] *Associate Professor, Department of Master of Computer Applications, BIET, Davangere*
[2] *Fourth semester Student, Department of MCA, BIET, Davangere*

Abstract—Brain hemorrhages is a critical medical disorder thatneeds to be diagnosed as soon as possible in order to allow for immediate medical attention. In the current study, we provide amachine approach to learning to detect various types of brain hemorrhage including subdural, epidural, and intracerebralhemorrhage using a Convolutional Neural Network (CNN) based ResNet-100 framework. We train and evaluate our CNN model usinga diverse data set of brain scans of normal cases and cases of stroke types. The application of the ResNet-100 algorithm comes from itsability to handle deep learning tasks and capture complex features inmedical images efficiently. Through extensive training andvalidation, our model achieves an impressive 95% accuracy inclassifying brain scans as normal or indicative of subdural, epidural,or intracerebral hemorrhage The high accuracy shows how wemachine learning approach is effective for multiclass brainhemorrhage detection. The proposed system has the potential to helpradiologists and healthcare professionals to accurately and effectivelyidentify various types of brain hemorrhage from medical imagesUsing the capabilities of CNN and ResNet-100, our method enables early detection and timely intervention, improving patient outcomes.
Keywords: Brain hemorrhage detection, CNN, ResNet-100, subduralhemorrhage, epidural hemorrhage, Intracerebral hemorrhage, accuracy

I. INTRODUCTION

Brain hemorrhage is a potentially life-threatening neurological circumstance. Its consequences in a huge burden on health resources. It can appear in lots of distinct reasons inclusive of because of multiplied blood strain, hemorrhage secondary to infarct, trauma, tumor hemorrhage, and plenty of more. One of the not unusual reasons of brain hemorrhage is traumatic brain damage. When the blood from trauma is in contact with adjacentmind tissues, it irritates and reasons swelling. This is known as cerebral edema. The pool of blood inside the mind parenchymais known as a hematoma. These reasons extended strain on the adjoining brain tissues which leads to reduced blood drift and kills the mind cells.

Brain hemorrhages can be distributed into several feathers grounded completely on their position and the underpinning motive. There are several typical types of brain bleeding. Subdural hematoma, intracerebral bleeding (ICH), subarachnoidbleeding (SAH), and epidural bleeding (EDH). Intracerebral hemorrhages (ICH) occurs whenever a blood vessel in the brainbreaks and leaks into the surrounding brain tissue. It's regularlyperforming from conditions similar as inordinate blood strain, trauma, or vascular deformations. Subarachnoid Hemorrhage SAH refers to bleeding within the space between the mind and the thin apkins that cover it called the subarachnoid space. It's typically due to the rupture of an aneurysm (a weakened blood vessel wall) or an arteriovenous contortion (AVM). Subdural Hematoma (SDH) happens whilst blood accumulates between the bottom of the brain and the dura mammy (the guarding membrane masking the mind). It's regularly due to trauma, which include a fall or head damage. Epidural Hematoma involves bleeding among the skull and the dura mammy. It generally happens due to trauma, which include a cranium fracture, which damages a roadway, leading to bleeding.

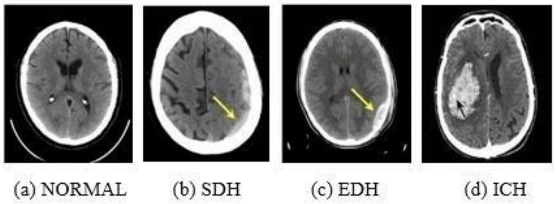

Figure 1:Non-contrast CT scan showing different subtypes ofintracranial hemorrhage

In recent years, machine learning has gained popularity, particularly deep learning, a branch of device learning which makes use of multi-layered neural networks. It shows enormouspotential to collect crucial information from imaging in medicine. Deep learning has been used in a few medical areas, such as the very accurate diagnosis of diabetic retinopathy on retinal fundus photos and the grading of metastases in histologicsections of lymph nodes. Convolutional neural networks (CNN)are primarily utilized in image classification and processing tasks where it has proven to be accurate. The head CT scan image will use the same technique.

Segmentation of the image will be needed, and the split image will be used to train an algorithm that uses deep learning to detect hemorrhages in the scan, which will be properly split into cases with and without hemorrhages.
Convolutional neural networks (CNNs), in particular, have shown great potential for improving the accuracy and efficiencyof the brain hemorrhage detection in CT scans. By analyzing large datasets of CT images that have been annotated by medicalexperts, CNNs can learn to identify subtle patterns and featuresthat are indicative of hemorrhage, allowing for more accurate and efficient detection.

By leveraging deep learning, CNNs may be skilled on great datasets of classified pics, letting them develop a sturdy expertise of the visible traits related to hemorrhages. This skilled version can then be hired as an AI tool to investigate medical images and highlight potential regions of issue for radiologists to check.

II. RELATED WORK

The term "intracranial hemorrhage" (ICH) describes bleeding that occurs inside the skull as a result of a blood vessel rupture.Due to the high death rates associated with ICH—up to 60% ofpatients pass away within 30 days, and a sizeable percentage doso within the first 24 hours after diagnosis—rapid investigationis essential. Due to its urgency, ICH must be diagnosed accurately and quickly since it is a medical emergency. The necessity for trustworthy imaging methods is highlighted by thefact that mistake rates for suspected ICH in general medical settings and emergency departments can be as high as 20% (Gross et al., 2019).[1]

The most accurate way to diagnose intracranial hemorrhage is through computed tomography (CT) neuroimaging of the brain, particularly during the first week after start. Accurate diagnosiscan be challenging since cerebral hemorrhaging visualization onCT scans depends upon density, amount, location, and their relationships with surrounding structures (Cohen, 1992). The time it takes to make a diagnosis and initiate therapy can be greatly shortened by including an automated method for identifying ICH in triage operations. Utilizing developments in artificial intelligence and image processing for automatic or semi-automatic identification of intracerebral hemorrhages in CT scans is the current focus of study in this field of study.[2]

For ICH identification, a number of models have been put out, some of which make use of the K-means and Fuzzy K-method (Bhaduria et al., 2013; Zeki et al., 2011), occasionally in conjunction with the Otsu methodology for segmenting regionsof interest (Loncaric et al., 1999). Other methods provide models based on weights, histogram level sets, and pixel depth (Liao etal., 2010), among others (Shahangianand Pourghassem, 2016).[3]

Morphological treatments have also been explored (Chan, 2007). Methods based on deep learning have also become morecommon in recent years for images classification jobs. Convolutional neural networks (CNNs) have been used in models by researchers to identify intracranial hemorrhages, hence overcoming the difficulties in ICH detection (Convolutional neural networks for detecting intracranialhemorrhaging CT images). For this article, utilizing its authors,copyright is 2020. Under Creative Commons License Attribution 4. Zero International (CC BY 4.0), use is authorized.[4]

A CNN-based approach has been set up by Wang et al. (2019) with the title "A Deep Learning Approach to HemorrhagicStroke Detection Using Convolutional Neural Networks." Their study focuses on finding hemorrhagic stroke in CT scans without contrast. The suggested approach proved the promise ofCNNs in this field by effectively identifying hemorrhagic strokewith high accuracy.[5]

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III. METHODOLGY

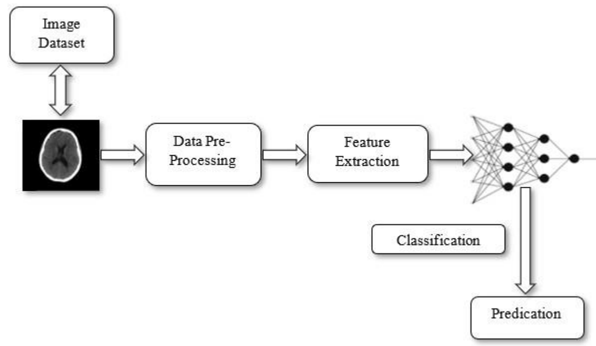

Figure 2:Block Diagram of Brain Hemorrhage Detection using CNN

A. Data Collection: To begin the system, it's far important to acquire a complete dataset of brain imaging statistics comprising both every day and hemorrhage instances. The records can be sourced fromKaggle, a famous platform for sharing datasets. It is crucial to make certain that the dataset selected isconsultant and numerous, incorporating diverse affected person populations, imaging modalities consisting of CT scans and MRI, and unique varieties of hemorrhages, which includes intracranial hemorrhage and subarachnoid hemorrhage. Byincorporating these factors, the dataset will provide a sturdy foundation for developing a powerful model forhemorrhage detection and analysis

B. Data Pre-Processing: The advised examination must include the Learning part of the CNN model, especiallyfor the scientific field wherein accurate identification of brain hemorrhages is essential. The CT scan image dataset requires significant consideration in terms of filtration and enhancements to enhance the mastering performance throughout the CNN version's training stage. Filtering, restructuring, and improving thequality of the dataset are all parts of preprocessing, which enhances the performance of models used for deep learning. In this study, several preprocessing approaches are employed to improve the quality and amount of data included in the images, including scaling, flipping, and augmenting images.

i. Resize the data: To make certain most suitable performance and prevent overfitting, deep studyingmodels require images of a regular length. By resizingimages to a standardized dimension, the studying manner is multiplied, and the likelihood of overfitting is decreased. However, resizing images can introduce challenges which include information loss, which could negatively affect version performance andaccuracy. In the cutting-edge examine, a resolution of 224 x 224 pixels is selected because the target size for image resizing. This option successfully resolves the overfitting and rapid learning rate problems, leading tohigher accuracy rates.

ii. Training and Testing Data: An essential phase in creating deep learning models is the train-test split., where the dataset is divided into appropriate proportions for training and testing. The dataset used inthis study consists of a total of 1,140 images belongingto four distinct classes. Out of these images, 950 are utilized for training the model, while the remaining 254images are reserved for testing and evaluating the model's performance. The dataset is carefully labeled to ensure that each image is assigned to the correct class. The four classes in the dataset represent differentcategories related to brain hemorrhage detection We can evaluate the model's performance on omitted data by dividing the dataset into testing and training subsets., ensuring a more reliable assessment of its ability to detect and classify brain hemorrhagesaccurately.

C. Feature Extraction: Extraction of relevant features fromthe brain images follows pre-processing. The process of feature extraction includes identifying informative characteristics or patterns that can discriminate between normal brain regions and hemorrhage regions.Various techniques mentioned earlier, It is possible to use features that are intensity-based, texture-based, shape-based, frequency domain-based, statistically- based, local, or deep learning-based. These techniquesanalyze the spatial and intensity variations within the brain images to extract discriminative features.

D.

i. Classification: Once the features are extracted, a classification algorithm is hired to classify the brain images into normal or hemorrhage classes. There are numerous classification methods available, which includes conventional machine learning algorithms Alternatively, deep learning fashions like convolutional neural networks (CNNs) may be appliedto analyze complicated styles and make predictions based totally on the extracted features. Theclassification model is trained on a categorized dataset, wherein the floor truth is understood (i.e., images are annotated as normal or hemorrhage). The trained model can then be used to predict the presence of hemorrhagein new, unseen brain images. Convolutional Neural Network: A Convolutional Neural Network (CNN) is a effective deep learning version specially designed for processing and reading structured grid-like data, which include images and motion images. CNNs use filters, additionally referredto as kernels, to analyze shared features via combiningfacts throughout different spatial dimensions or channels. A series of deep convolutional layers are used to learn and extract these characteristics.CNNs include pooling layers in addition to convolutional layers to speed up the data flow and simplify the representation.For instance, max pooling entails examining a matrix of images pixels, generally in a 2x2 window, and deciding on the maximum activation cost within that region. This pooling operation reduces the spatial dimensions while keeping the presence of essential functions. In the final stage, the pooling layer's output offers a scalar price that denotes the presence of a particular feature.

A fully connected or dense layer with the same range of neurons as the number of classes in the task is frequently included in the final layer of a CNN. This layer creates predictions by categorising a picture into distinct groups using the knowledge gained from the preceding levels.Various computer vision applications, such as image classification, object recognition, and picture segmentation, have seen great success withCNNs.

ii. Transfer Learning (Pre-trained model):Transfer learning also can be implemented to the challenge of brain hemorrhage detection the use of deep learning models. Can make use of transfer mastering for brain hemorrhage detection through acquiring a Pre-trained Model and Searching for a deep learning model that hasalready been trained that has been trained on a sizable medical imaging dataset, ideally which include brain images. Some usually used pre-trained models for medical imaging tasks include architectures like VGG,ResNet, or DenseNet. By making use of transfer learning to brain hemorrhage detection, we can have benefit from the generalization abilities of pre-trained models even with limited medical imaging data. It canhelp improve the detection method's precision and effectiveness, supporting medical professionals in identifying and treating brain hemorrhages. In pre-trained deep learning model, we used ResNet50 architecture.

iii. ResNet 100: ResNet-100 is a CNN architecture. The 100 in ResNet-100 denotes the network's total numberof layers. It consists of 100 layers, includes skip connections (also known as residual connections), convolutional layers, pooling layers, fully connected layers, and so on. When the use of ResNet-100 for responsibilities like image classification, the network takes an input image and procedures it through a sequence of convolutional layers with different filter sizes, followed through activation functions andpooling layers to extract relevant features. To generate the expected options for different categories, the gathered features are subsequently processed via fully connected layers and a final SoftMax layer. Benefit ofResNet-50 is its pre-trained models, which have been trained on big-scale datasets like ImageNet. To use ResNet-50, we have to either train the network from scratch dataset or utilize pre-trained models furnished by way of frameworks like PyTorch or TensorFlow.

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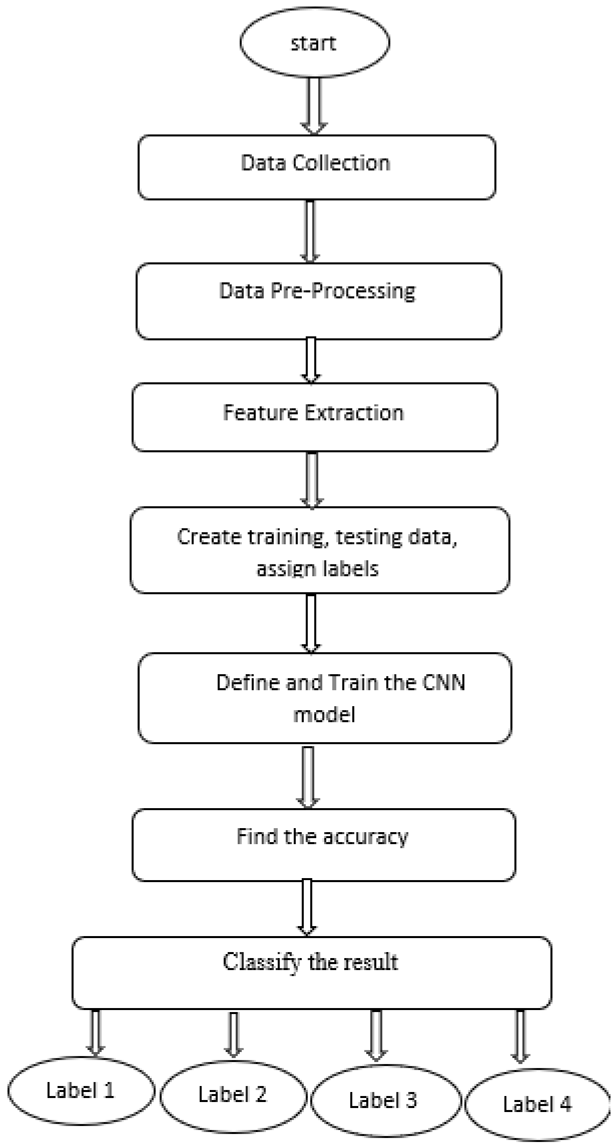

Figure 3:Flowchart of Brain Hemorrhage Detection using CNN

IV. RESULTS AND DISCUSSION

The study aimed to develop a CNN with the usage of theResNet- 100 architecture to identify and classify one-of-a-kind subtypes of brain hemorrhage, inclusive of subduralhemorrhage, epidural hemorrhage, intracerebral hemorrhage,and normal brain CT. The CNN model done an excellent accuracy of 95% in as it should be identifying the hemorrhage subtypes.
Accuracy and loss graphs provide a visual representation of themodel's performance during of each training and testing phases. The accuracy graph demonstrates the improvement of accuracyover epochs, whilst the loss graph illustrates the decreasing fashion of model errors. The testing and training dataset accuracy and loss variance for the models used in the current study are shown in the graphs below.

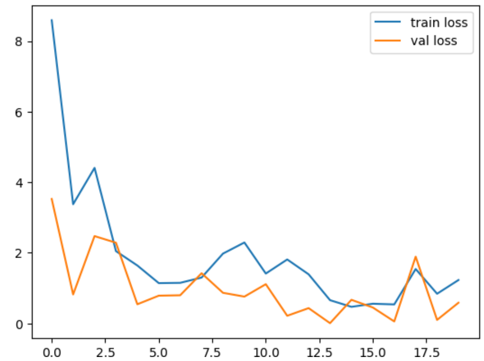

Figure 4:Training Phase Loss Variation: Validation Set

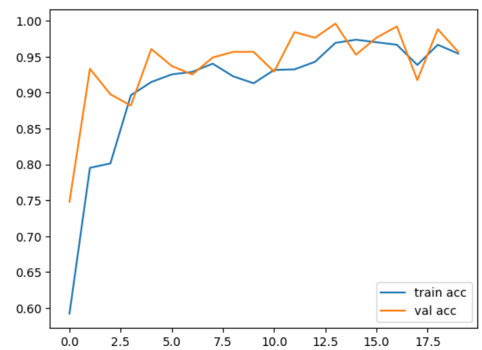

Figure 5:Training Phase accuracy Variation: Validation Set

To make the results accessible and user-friendly, a web-based interface was implemented. This interface allowed users toupload brain CT scans and obtain the predicted classification ofthe hemorrhage subtype. The web interface presented the resultsin a clear and intuitive manner, providing valuable information to clinicians and radiologists for further diagnosis and treatmentplanning.

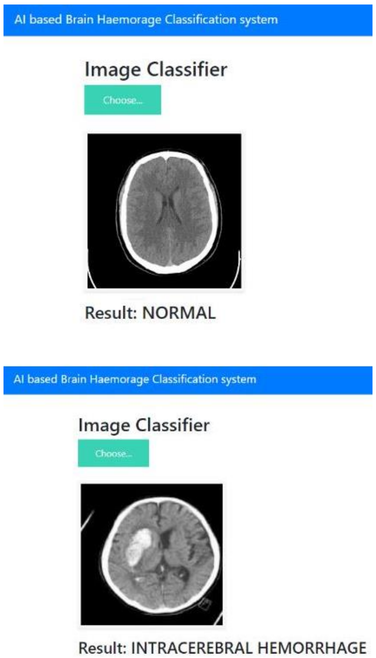

Figure 6:Screenshots of detection of normal and brainhemorrhage

V. CONCLUSION

The deep learning-based CNN with the ResNet-100 architecturedemonstrated promising consequences in correctly detecting and classifying brain hemorrhage subtypes, attaining an accuracy of95%. The web interface supplied a convenient and human- friendly platform for clinicians to utilize the model and achievepredictions for the hemorrhage subtype from uploaded brain CTscans. The aggregate of superior deep learning techniques and web-based interfaces has the capability to improve the performance and accuracy of brain hemorrhage diagnosis and treatment. Further research and validation are important to absolutely recognize the model's overall performance and its impact on medical practice.

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