Pre-thesis-II Report

Detection of Intracranial Hemorrhage on CT Scan Images Using Convolutional Neural Network

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Abstract

Intracranial hemorrhage is bleeding within the skull which can damage the brain tissue and cause disability or death. It is a serious medical condition that occurs when blood is built up within the skull after a blood vessel is ruptured. Brain damage can be minimized if intracranial hemorrhage is diagnosed immediately, and the patient may regain mobility. Deploying applications of AI in clinical medicine to accelerate the accuracy of intracranial hemorrhage diagnosis aims to minimize the severity of the condition, therefore, enhancing medical care. Adequate analysis of the CT scan imaging is integral for diagnosis and management. Deep Learning, which is a subset of AI, is widely used in interpreting medical images and has shown promising advancements in diagnosing an intracranial hemorrhage. With time playing a crucial factor, automatic lesion identification is one of the most important factors in precision medicine dealing with huge datasets of neuroimaging compared to manual lesion segmentation. This paper will look into a Deep Learning method which uses Convolutional Neural Network on neuroimaging to assist in the diagnosis of intracranial hemorrhage.

I. Introduction

With the advent of technology surging through all spheres of life, Artificial Intelligence has undoubtedly revolutionized many domains, with its largest impact in the healthcare industry. Integrating AI in the healthcare ecosystem has paved the way for continual growth and improvement in the medicine field and an increased revenue potential.

The healthcare industry continues to evolve as the application of AI becomes more prevalent and allows for a multitude of benefits, from analyzing big patient data sets to automating tasks so as to deliver better healthcare faster. Machine Learning, a subset of AI, has shown potential to provide data-driven clinical decision support by using data and algorithms to give invaluable automated insights to physicians and healthcare specialists.

The brain is the most complex organ in the human body. An Intracranial hemorrhage occurs when a blood vessel is ruptured in the brain and blood starts to build up within the skull [17]. It is a medical emergency because brain cells begin to die as pressure is built up within the skull and the oxygen supply becomes limited. Prompt treatment is crucial to minimize the damage and save lives.

Computed Tomography (CT) of the head is the preferred procedure as the first step to assess a stroke patient so as to determine whether the individual is experiencing an Intracranial Hemorrhage. Currently the standard approach is manual lesion delineation which is both operator-dependent and time-consuming.

Deep learning is a subfield of machine learning based on artificial neural networks with representation learning. The medical field has greatly benefited from the use of deep learning models which saves time and produces accurate results. Our research is mainly focusing on how to automate the detection of Intracranial Hemorrhage using CT scan images. We aim to present a method that uses a Convolutional Neural Network (CNN) model that can automatically delineate infarct and bleeding in Intracranial Hemorrhage CT images.

A) Problem Statement

As of today, stroke is a leading cause of serious long-term disability in adults. With a globally ageing population estimated to triple by the year 2050, neurophysiological investigation of patients suffering from stroke with advances of AI in cognitive neuroscience will evolve our understanding of the most complex human organ.

The typology of stroke is classified into two categories: Ischemic and Hemorrhagic. Ischemic stroke is the most common type of stroke which is caused by a blood clot that blocks the brain's blood vessels. Nearly 87 percent of all strokes are ischemic stroke [1]. Hemorrhagic stroke is another major type of stroke in which the blood vessel of a brain ruptures and causes bleeding. It makes up about 13 percent of all strokes. This type of stroke is directly caused by Intracranial hemorrhages [18]. Intracerebral hemorrhage, which is a subtype of intracranial hemorrhage, occurs at a rate of 24.6 per 100,000 people in the world [17].

The two modalities regularly used for brain lesion mapping are computed tomography (CT) and magnetic resonance imaging (MRI). With time playing a crucial factor, CT is the preferred procedure with the advantages of speed, cost and reduced exclusion criteria relative to MR imaging. The current method for lesion identification is still manual that puts forward a number of disadvantages [2]. Even though hemorrhagic stroke appears more clearly on a CT scan image, lesion identification of the more common ischemic stroke takes nearly over a day using the manual delineation approach. Ischemic stroke is difficult or nearly impossible to see in CT images, especially during the first few hours after the stroke occurs, which is the period when treatment decisions are most vital. This means that by the time the region of the abnormal brain tissue is localized, delay of treatment propels the brain damage thus likely to worsen the individual's chances to regain mobility.

With the availability of big medical data sets and development of complex algorithms, AI has made an immense impact in the healthcare industry by recognizing the need for personalized care and earliest definitive diagnosis. Related research and extensive workings in this specific direction have been mostly done using MRI [5]. This is because of MRI producing clearer and detailed images compared to CT [3] and the relative limitations posed by CT images as mentioned by [4].

However, taking into consideration the advantages of CT images that outweighed that of MRI in case of quick diagnosis as we have mentioned earlier has directed us to work on the problem based on CT images. Our intent is to deploy the deep learning frameworks that have shown great accuracy results and integrate that architecture to CT images and eventually figure out promising results.

Therefore, this research will attempt to employ a deep learning algorithm, specifically Convolutional Neural Network (CNN) on CT scan images to automate the Intracranial Hemorrhage lesion segmentation and thus enhancing an effective clinical diagnosis.

B) Research Objectives

As today's medical industry continues to evolve, the notion of computer-based clinical decision support has accelerated as a dominant topic in informatics research so as to improve the quality of decision-making in healthcare. AI has the potential to optimize personalized care by facilitating diagnosis and therapeutic decisions. Hence, we aim to find a way to develop an understanding of how incorporating the applications of AI accelerates the diagnosis of intracranial hemorrhage and create a solution that leverages on data accuracy for improved decision-making. Our goal is to develop a solution using Image Processing with Deep Learning model, specifically a Convolutional Neural Network model that will assist healthcare specialists to make an improved diagnosis.

The objectives of our research are:

- To thoroughly understand the applications of AI and how it works in our interested domain
- To deeply understand Convolutional Neural Network models and contrast their usage in different scenarios of our solution
- To develop a model for automatic lesion delineation using CT scan images
- To evaluate the model
- To offer recommendations on improving the model

II. Literature Review

Currently, stroke is one of the costliest diseases from human, family and societal perspectives. Starting from human costs, stroke is also a leading cause of death and disability. About 16 million first-ever strokes occur in the world, which causes a total of 5.7 million deaths throughout a year [6]. Higashida and Chair (2003) gave definitions for two types of stroke. They are : ischemic stroke and hemorrhagic stroke. An ischemic stroke is any damage to the brain which is caused by lack of blood flow in brain blood vessels or in major arteries that lead to the brain. This stroke usually results in temporary or permanent loss of one or more normal functions of the body [7]. On the other hand, A hemorrhagic stroke is a damage to the brain caused due to the bleeding into the brain [7]. Hemorrhagic strokes are mostly caused by bleeding through ruptured blood vessels within the brain which is a condition known as intracranial hemorrhage [17]. The ischemic stroke accounts for nearly 80 percent of all strokes and Hemorrhagic strokes account for about 20 percent of strokes [7].

Computed tomography scan or CT scan has proven to be a great and efficient technique in detecting strokes especially with hemorrhage strokes. In a study, it is said that for the hemorrhage type classification, more than 92% accuracy is achieved in identifying hemorrhage strokes by CT scans [8]. CT Scan is considered to be very efficient and useful in detecting the internal bleeding of a brain that occurs in hemorrhagic brain stroke. However, in cases in which the patient is having an ischemic stroke it may be quite difficult or may even be impossible to track the bleeding in the brain with the help of CT scan. In such times when the CT scan fails show an ischemic stroke and the neuroradiologists are strongly suspecting that the patient is having a brain stroke whereas in the reports of CT scan, no signs of hemorrhagic stroke was detected, they often use IV TPA to the patient [11].

According to Baird et al. (2009), Computed tomography Scan-CT Scan is considered to be the gold standard for the clear-cut exclusion of brain hemorrhage. But When it comes to the remaining acute ischemic signs, it is slightly more open to debate [9]. Over the years there has been notable progress in scanner hardware, and these new CT units now allow to scan the entire human brain in just a few seconds [10].

However, another tool has been introduced to improve the performance of CT scan for ischemic stroke called multiphase CT angiography which is an imaging tool that provides three time-resolved images of pial arterial filling in the whole brain, unlike conventional single-phase CT angiography [10]. It has shown great promise in predicting the clinical outcomes in patients with acute ischemic stroke [10]. The results of multiphase CT angiography were quite promising.

In a study of 147 patients, for multiphase CT angiography the inter-rater reliability is excellent (n = 30, k = 0.81, P , .001) [10]. Clinical outcome predictability is quite modest at the receiving operating characteristic curve analysis (C statistic = 0.56, 95% confidence interval [CI]: 0.52, 0.63 for 50% decrease in NIHSS over 24 hours; C statistic = 0.6, 95% CI: 0.53, 0.68 for 90-day mRS score of 0–2) hence it is better than that of models using single-phase CT angiography and perfusion CT (P , .05 overall). With AIC and BIC, models that are using multiphase CT angiography are better than models using single-phase CT angiography and perfusion CT with a decrease of 50% or more in NIHSS over 24 hours (AIC = 166, BIC = 171.7; values were lowest for multiphase CT angiography) and a 90-day mRS score of 0–2 (AIC = 132.1, BIC = 137.4; values were lowest for multiphase CT angiography) [10].

Takahashi et al. (2014) designed a method called MCA dot sign which was used for classifying images using an SVM with four features. 297 CT images from seven patients with an MCA dot sign were used in the process. This study was able to gain a maximum sensitivity of 97.5% which had a false positive rate of 1.28 per image and 0.5 per hemisphere while assessing the MCA dot sign on CT scan images which were unenhanced [12]. However, their use of unenhanced images can be problematic as they might create distortion in the results.

Forkert et al. (2015) used 12 SVM classification models for predicting the mRS score of ischemic stroke patients with parameters such as lesions in different brain regions, NIHSS at admission, and patient age. An mRS prediction was obtained which had a multi-value accuracy of 56%, and another dichotomized mRS was obtained with a prediction accuracy of 85% [13]. However, they selected patients with a balanced distribution of mRS scores which is not the same as a real-life distribution of mRS scores. Using CT scan images, early detection of ischemic strokes was done by Rajni and Bhavani (2013) with segmentation, midline shift and image feature characteristics. They used SVM, k-NN, ANN and decision tree with accuracy scores respectively 98%, 97%, 96% and 92% [14]. Though their accuracy scores were good, they used a small sample size which consisted of 15 stroke cases and 6 normal cases.

Hemispheric ischemic stroke happens due to the blockage of a blood vessel and the patient's outcome is directly related to the final size of the ischemic infarct i.e. the severity of damage to the brain parenchyma. Generally, MRI T2-weighted imaging (T2WI MRI) at 3 months post-ictus is considered the gold standard for the measure of tissue recovery and the patient outcome [15]. Although, unsupervised clustering technique such as ISODATA (Iterative Self-Organizing Data Analysis) can be used to combine MRI data sets from the acute phase and the sub-acute phase post-stroke to predict final infarct volume and produce a time-independent surrogate MRI outcome predictor [15]. However, ISODATA has some significant drawbacks. Maps produced by ISODATA are not approximately continuous and do not produce an easily visualized association between the map and the outcome measure. [15] Furthermore, ISODATA is unstable in the presence of image artifacts and noise. However, the Artificial Neural Network (ANN) model is useful to predict the stroke outcome [15]. An ANN model was used to combine the clinical and imaging variables National Institutes of Health Stroke Scale (NIHSS) and DWI images to determine the final infarct volume of patients treated with IV rt-PA (recombinant Tissue Plasminogen Activator), and the ANN was completely able to predict the tissue fate. The ANN technique provides a very fast (essentially real-time), approximately continuous, and intuitive mapping of the predicted outcome, while preserving the time-independent and multi-parametric strengths of clustering approaches.

When it comes to hemorrhagic strokes, detecting the presence of intracranial hemorrhage is crucial, as it is the clearest sign of a hemorrhagic stroke. Arbabshirani et al. (2018) deployed a CNN model to detect intracranial hemorrhage on 37,074 CT scan images and obtained an accuracy of 95% [19]. However, their model does not specify in which area of the brain the hemorrhage has occurred. Lee et al. (2020) used an ANN model on 9085 CT images and found an AUC of 0.859 [20]. However, as they didn't use a CNN-based model, they didn't perform any data pre-processing or selection.

III. Proposed Model

In our proposed system, we are building a Convolutional Neural Network (CNN) model consisting of multiple layers that can identify and classify the images of two predefined classes: 1. Intracranial Hemorrhage and 2. No Hemorrhage. We obtained our dataset from the Physionet repository [16].

Generally, most of the machine learning applications require GPU (Graphics processing unit) as a large number of computation takes place on quite a big amount of data. GPUs are considered to have almost 200 times more processors than an ordinary CPU [21]. This helps improve the performance of the neural networks. Hence we opted to use Google colaboratory's shared GPU to run our CNN model.

There are numerous open source libraries that focus on better machine learning results. Some of the popular ones are : Scikit-learn, OpenCV, PyTorch and TensorFlow. In order to boost the performance of our proposed model, we opted to use TensorFlow which is a popular open source library that helps to develop and train machine learning models. We also used Keras to Take advantage of the full deployment capabilities of the TensorFlow platform. Apart from these, we used several other modules and libraries such as Os, seaborn, pathlib etc.

For our proposed system, we have a dataset consisting of 2501 labelled images. After splitting the dataset for training and validation, we had 2000 images as our training data and 501 images as our validation data.

As for our Convolutional neural network (CNN) model, we are building sequential models consisting of multiple 2D layers. The proposed approach flowchart is illustrated in Figure 1.

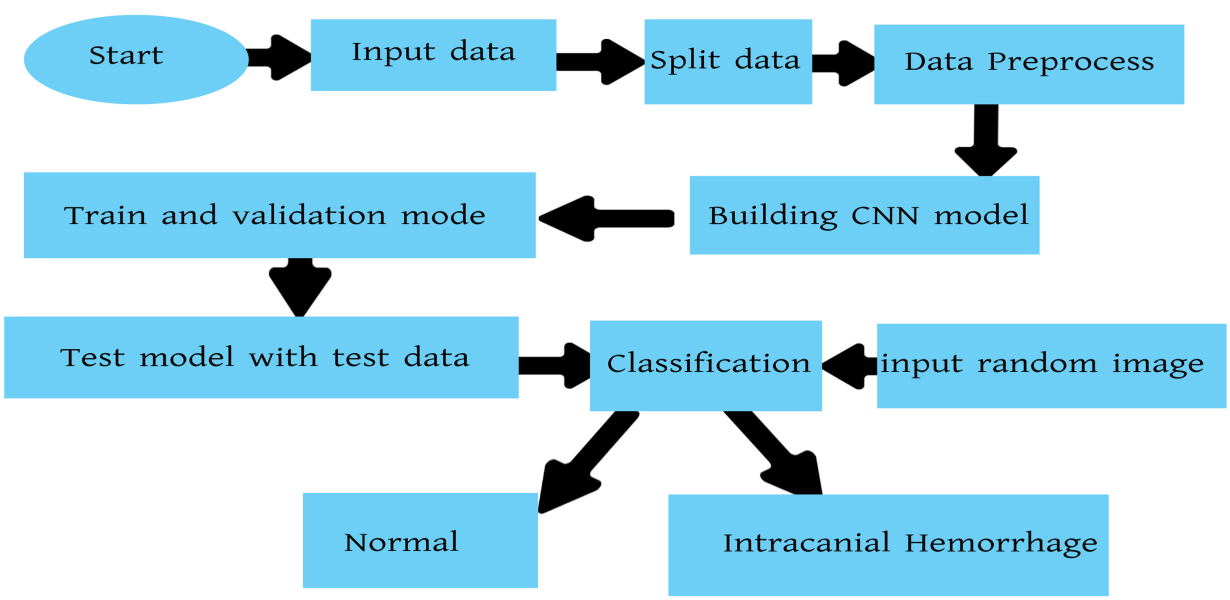


Figure 1. Flowchart of the proposed model

The proposed approach includes essentially the following steps :-

- Data Analysis
  - Input Data
  - Data Preprocessing
- Architecture of the Model using CNN
  - CNN Model
  - Convolutional layer
  - Pooling layer
  - Fully Connected Layer

3.1 Data Analysis

Data analysis is an important step for any research. For our proposed system, We have categorized our data analysis into two parts- Input Data and Data Preprocessing.

3.1.1 Input Data

In the automatic diagnosing process of segmenting the Intracranial Hemorrhage (ICH) regions and identifying the skull fracture, deep learning algorithms possess the potential ability in providing the diagnosis of Intracranial Hemorrhage (ICH) with great accuracy [16]. Convolutional neural networks (CNN) in its class of all other deep neural networks have performed excellently in recognizing multiple image classification and segmentation in automated tasks. [16]. The CNN takes input data of the image's raw pixel and extracts the features and successfully infers about the object [22].

A retrospective study was conducted (approved by the Research and Ethics Board in Iraqi ministry of health-Babil Office) in Al Hilla Teaching Hospital-Iraq between February and August 2018 [23]. CT scans were gathered which had the properties of an isotropic resolution of 0.33 mm, 100 kV, and a slice thickness of 5mm [23]. We have collected this dataset from Physionet repository [16]. This dataset consists of 82 patients among which 46 were male subjects and 36 female subjects (refer to Table 1 for the subject demographics)[23]. The dataset used contains head CT (Computed Tomography) scan images in JPG format [16]. Out of the 82 subjects 31 patients were diagnosed with ICH.

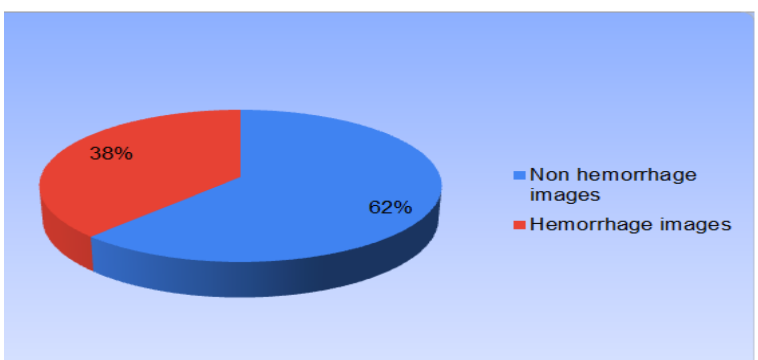
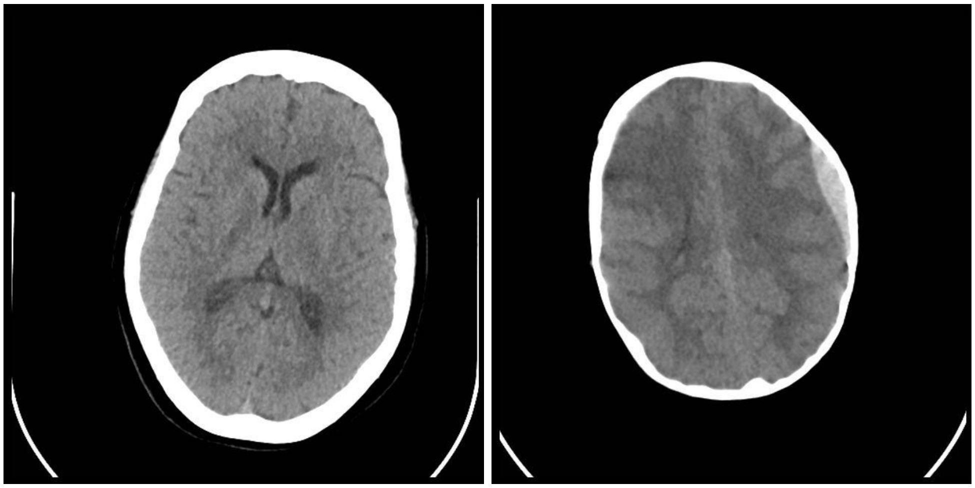


Figure 2. Hemorrhage patients and non hemorrhage patients



(a) (b)

Figure 3. (a) CT image of a healthy brain, (b) CT image of a brain with Intracranial Hemorrhage

There were 2501 brain CT scan images and 2500 bone images for the 82 patients. Approximately 30 images per patient were available [16]. Later the 2500 bone images were discarded as only brain images were needed to train the proposed CNN model. The remaining 2501 brain images were assembled into two groups - 950 images with Hemorrhage and 1551 images with no Hemorrhage (refer to Figure 2), used in the training process.

Table 1: Subject demographics

Total number of subjects	82	**Sex (Male, Female)**	46M, 36F
Age(years)	27.8 ± 19.5	**Age range**	1day – 72 years
Number of subjects (age < 18years, age ≥ 18years)	27 , 55	**Number of subjects with ICH**	31

3.1.2 Data Preprocessing

Data preprocessing is an important step for preparing the data for applying it in the Convolutional Neural Network (CNN) algorithm. This process is basically used to remove the variables that do not contribute in improving the results or accuracy of the CNN model. Moreover, this step allows us to make all necessary transformations on the raw data that can help in improving the performance of the CNN model to give better results and accuracy. For our proposed system, detecting intracranial hemorrhage by CT scan images, we initially split our image dataset of brain CT images consisting of both normal and intracranial hemorrhage images in separate folders into two parts: 1. Training dataset and 2. Validation dataset. We put 80% of the images into the training dataset which is precisely 2000 images and the rest of 20% images went to the validation dataset which is 501 images to be precise.

Furthermore, we have applied some transformation to our training dataset. This transformation includes setting the images' sizes, batch size, rescaling, rotation, zooming and horizontal flip.The values set for all of these are :

- Image size : 256x256
- Batch size : 16
- Rescaling size : 1/255.0
- Rotation : 30 deg
- Zoom range : 0.4
- Horizontal Flip : enabled

We have used 'binary' class mode here as our classification result falls in one of the two classes i.e. 'Intracranial Hemorrhage Detected' or 'Normal'.

As for our validation dataset, we applied the same image and batch size to it as well. We have also kept the class mode 'binary'.

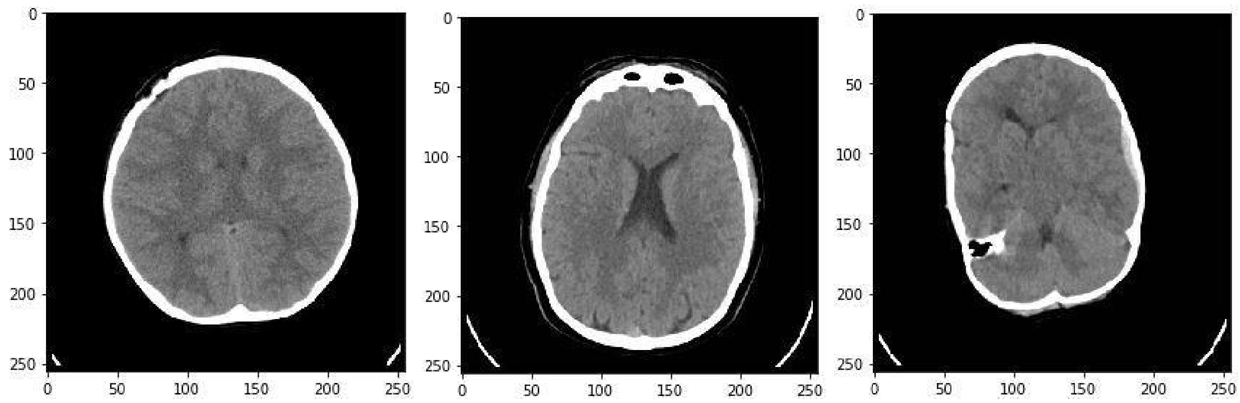


Figure 4. Before Preprocessing

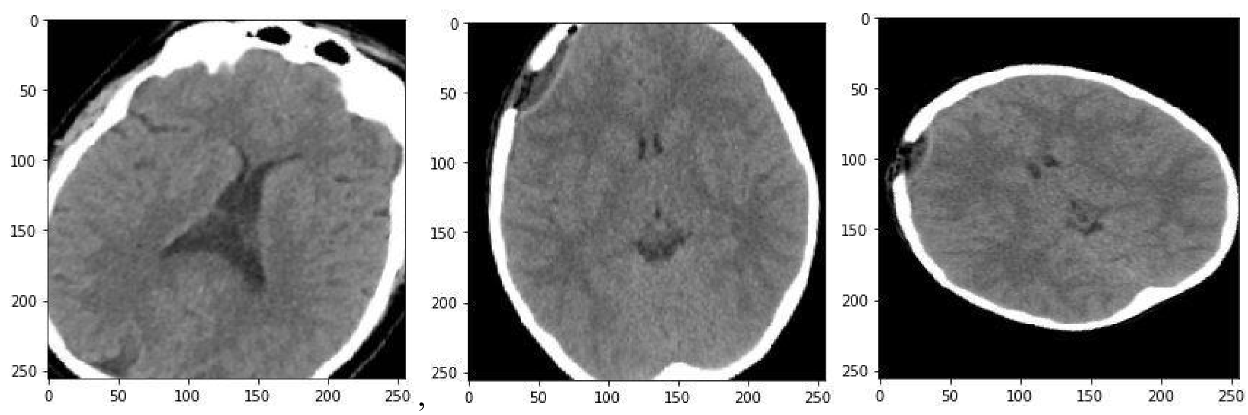


Figure 5. After Preprocessing

After carefully applying these transformations to our raw dataset in order to improve the performance of the CNN model, we moved to the next step that is creating the Convolutional Neural Network model where we can run the dataset for machine learning.

3.2 Architecture of the Model Using CNN

Deep Learning is a subset of machine learning inspired by the structure of the human brain which uses hierarchical neural networks to analyze data. It is concerned with algorithms that mimic and replicate the workings of the human brain in processing data and creating patterns that hold useful in decision making.

Convolutional Neural Network is one of the most popular deep learning algorithms that is commonly applied to analyze visual imagery. It has had groundbreaking results over the past decade in a variety of fields from image recognition to voice recognition [24]. This achievement of Convolutional Neural Network (CNN) has prompted and inspired us to create our model with CNN for the proposed system of detecting Intracranial Hemorrhage.

Basically, a CNN is built up with three layers. Convolutional layers, Pooling layers and fully-connected (FC) layers. A CNN architecture gets formed when all these layers are stacked. In addition to these three layers, there are two more important parameters, Dropout layer and Activation function. Both convolution and pooling layers help to separate and identify the various features of the input image for analysis. This feature is called Feature Extraction and the connected layer utilizes the output from the convolution process and predicts the class of the image. This process is known as Classification.

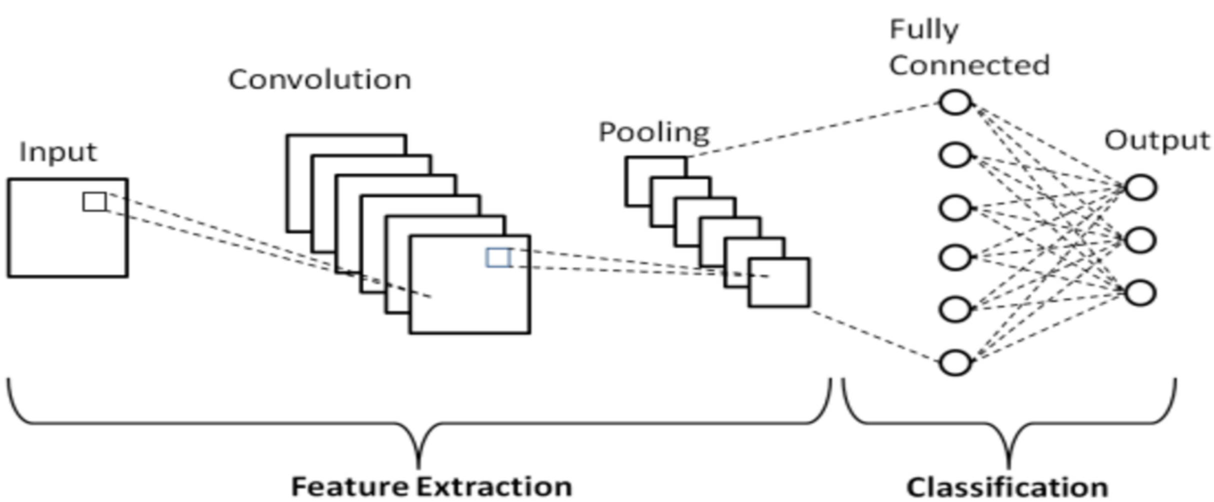


Figure 6. Architecture of a CNN Model [25]

After splitting the dataset into train data and validation data, we created a sequential CNN model for the proposed system using a neural network library called Keras. We added three 2D convolutional layers and the same number of max pooling layers to our model. After that, we added two layers of dense and one layer of flatten. Finally, we obtained precisely 13,086,913 trainable params for the model to train the images.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 254, 254, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 127, 127, 32)      0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 125, 125, 64)      18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 62, 62, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 60, 60, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 30, 30, 128)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 28, 28, 128)       147584
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 14, 14, 128)       0
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 512)               12845568
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 513
=================================================================
Total params: 13,086,913
Trainable params: 13,086,913
Non-trainable params: 0
_________________________________________________________________
```

Figure 7. CNN model for detecting Intracranial Hemorrhage

3.2.1 Convolutional Layer

For our proposed system, we have used three layers of 2D convolutional layers. For the first layer, we had given an input size of size 256x256 in order to match with the size of our input images. We had set our kernel as 32 for this layer and used ‘relu’ activation. It gave us an output shape (254, 254, 32).

$$Wout = \frac{W-k+2p}{S} + 1 \qquad Wout = \frac{(256-3+2*0)}{1} + 1 \quad (1)$$

Formula for output size in Convolution layer

For the second and third layers, we increased our kernels to 64 and 128. It gave output shapes (125, 125, 64) and (60, 60, 128) respectively.

3.2.2 Pooling Layer

Pooling Layer acts as a bridge between the Convolutional Layer and the Fully Connected Layer. In our model, we used a max pooling method. The initial target was for this to decrease the size of the convolved feature map to reduce the computational costs.

3.2.3 Fully Connected Layer

The Fully Connected (FC) layer incorporates the weights and biases and also the neurons. This layer is used for the connection between other two different layers. This layer basically helps the classification process to take place. In this step, we used two Dense layers and one Flatten layer.

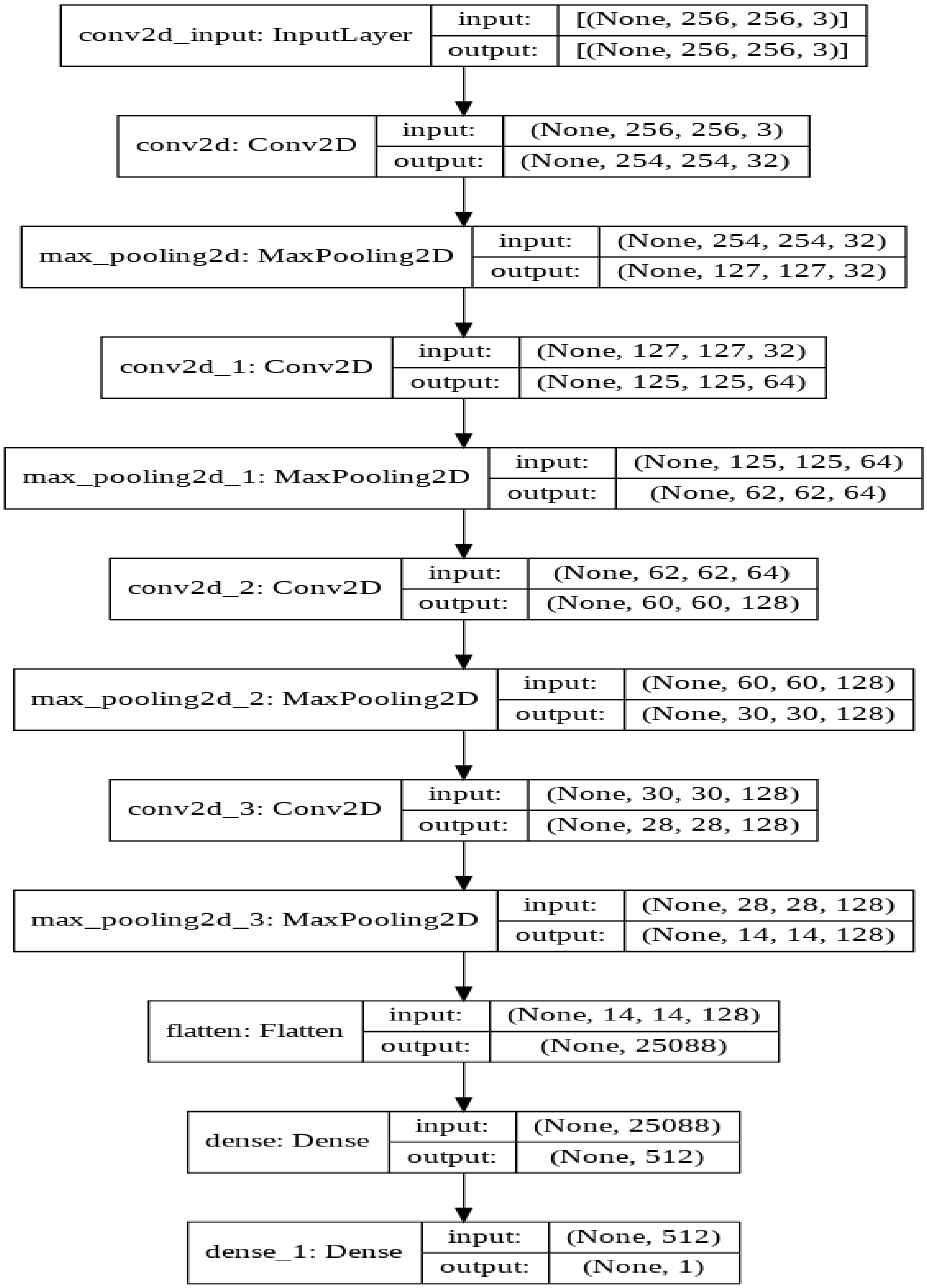


Figure 8. Visual Representation of the CNN Model

IV. Outcome

After creating the CNN model for our proposed system, we went ahead to train and validate our processed dataset in the model. We ran 125 epochs for training. After the training, we had achieved an accuracy of 83.85000% on the training dataset and a validation accuracy of 73.0538%. The result is very promising and encouraging. However, We intend to get better results in future as necessary modifications will be made to the model as well as in the dataset, that will help increase the accuracy of the training model. The below figures show the plotted graph of training accuracy and validations loss.

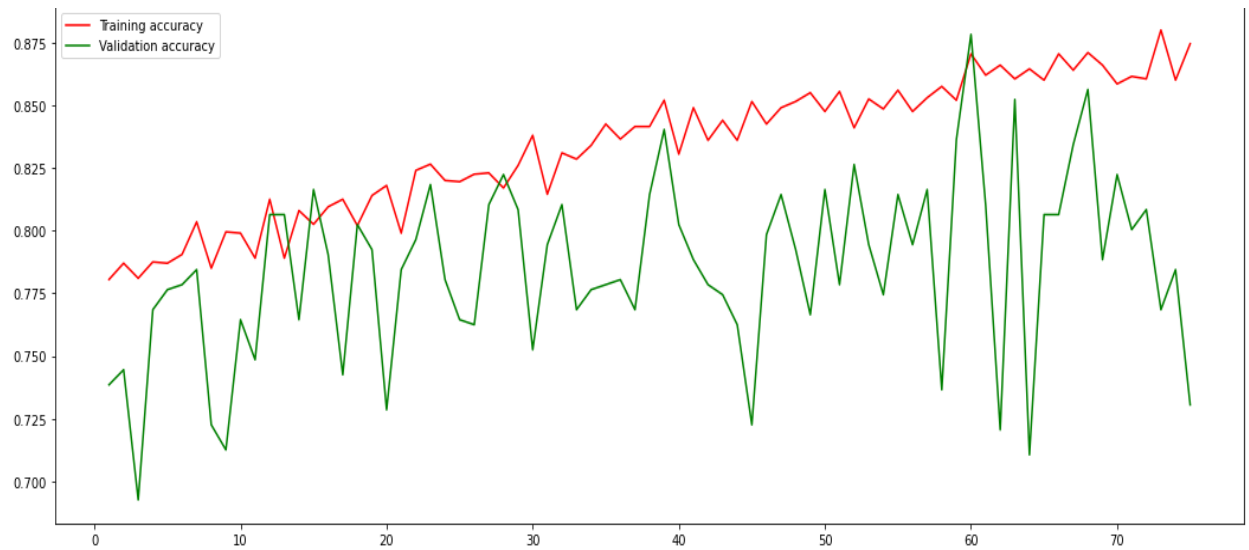


Figure 9. Training and validation accuracy

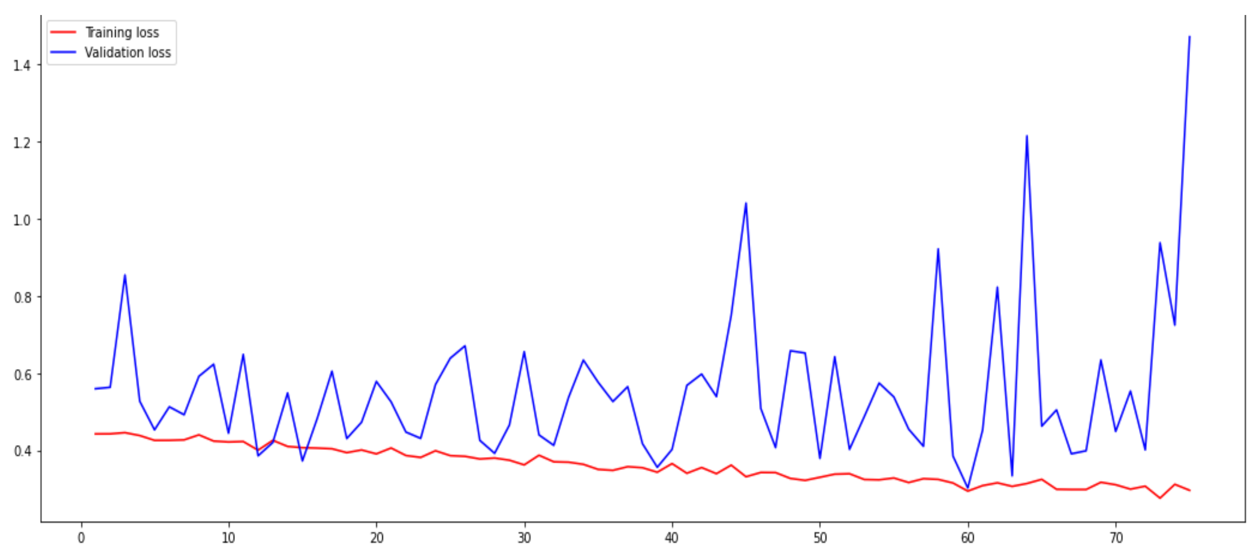


Figure 10. Training and validation loss

V. Conclusion

Health is the greatest asset and advances in technology have been profoundly shaping healthcare by opening up more avenues of extensive research and exploration to improve the quality of life. Our research wanted to address the challenge of a leading life-threatening medical emergency and figure out how incorporating AI in this sphere could help to assist healthcare experts for an improved and effective clinical diagnosis. With our work we hope to provide a solution that detects and narrows down the lesion delineation on CT scan images of the commonly occurring intracranial hemorrhage. So far, in our proposed CNN model, we have achieved an accuracy of 83.85% and validation accuracy of 73.0538%. However, we are still looking to improve these results. We believe that by accomplishing our goal, not only will we be able to use technology to help individuals suffering from intracranial hemorrhage but also better our understanding of the most complex organ of the human body.

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