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Detection of intracranial bleeding using an effective neural network

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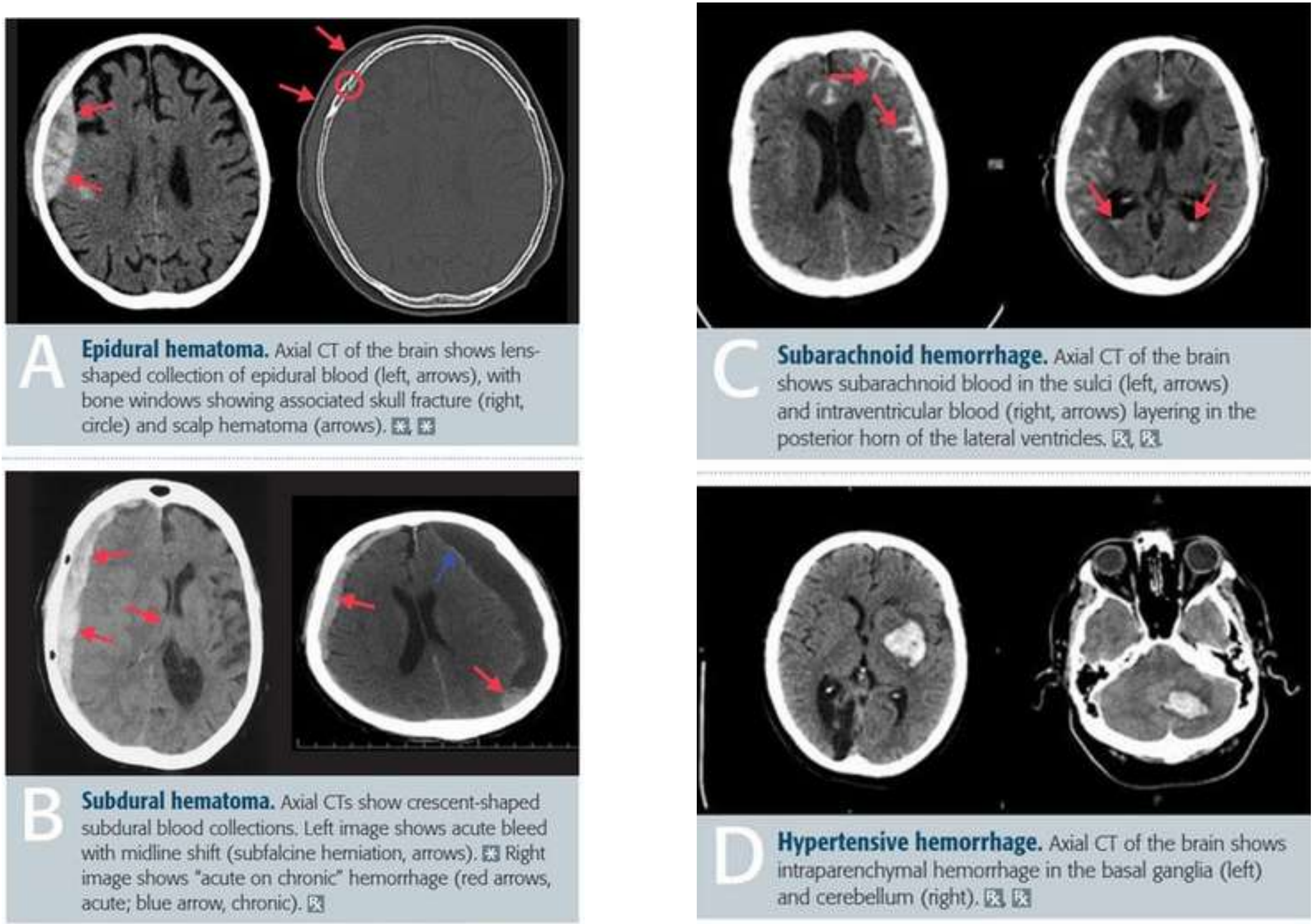
Objective

- To detect and classify various types of Intracranial Bleeding using neural networks.

PROBLEM STATEMENT:

- Intracranial bleeding that occurs inside the Cranium, is a serious health problem requiring rapid and often intensive medical treatment and diagnosis of this is often time consuming. The diagnosis can be done by using neural networks that can detect the bleeding in the CT scan and predict the type of the hemorrhage thereby reducing the time needed for the detection of intracranial hemorrhages in normal cases.

Types of Intracranial Bleeding



Source: https://www.grepmed.com

Proposed Solution

- System with much better accuracy for detecting the various types of Intracranial bleeding by comparing with two neural networks.

  Alexnet

  Modified CNN

Literature survey

S.No	Authors	Title of the research work	Journal Name / Year	Inference
1	M. Li, L. Kuang, S. Xu and Z. Sha	Brain Tumor Detection Based on Multimodal Information Fusion and Convolutional Neural Network	IEEE Access/ 2018	The system that extends 2D-CNN to 3D-CNN to extract better difference in the modalities.
2	Y. Liu et al	Deep C-LSTM Neural Network for Epileptic Seizure and Tumor Detection Using High-Dimension EEG Signals	IEEE Access/ 2020	A system uses convolutional long short-term memory (C-LSTM) neural network to obtain better recognition of seizures and tumors in the case of epilepsy

Literature survey

S.No	Authors	Title of the paper	Journal Name / Year	Inference
3	H. H. Sultan, N. M. Salem and W. Al-Atabany	Multi-Classification of Brain Tumor Images Using Deep Neural Network	IEEE Access/2019	Deep Learning model based on a convolutional neural network is proposed to classify different brain tumor types using two publicly available datasets
4	Ye, H., Gao, F., Yin, Y. et al.	Precise diagnosis of intracranial hemorrhage and subtypes using a three-dimensional joint convolutional and recurrent neural network	Eur Radiol /2019	A joint CNN-RNN classification framework is proposed with flexibility to train when subject level or slice level labels are available.

Literature survey

S.No	Authors	Title of the paper	Journal Name / Year	Inference
5	Satya Singh, Lipo Wang, Sukrit Gupta, Haveesh Goli, Parasuraman Padmanabhan, and Balazs Gulyas	Deep Learning on Medical Images: A Review	IEEE Access/*2020*	Two model variants are proposed, one of which is the 3D VGGNet architectures, Resnet, and the proposed method enhances classification performance significantly
6	Woniak, M., Sika, J., and Wieczorek,M.	Deep neural network correlation learning mechanism for CT brain tumour detection	Applicative Neural Computing /2021	The support neural network aids CNN in deciding which filers are best for pooling and convolution layers. As a result, the main neural classifier learns faster and is more effective

Literature survey

S.No	Authors	Title of the paper	Journal Name / Year	Inference
7	P. Kumar Mallick, S. H. Ryu, S. K. Satapathy, S. Mishra, G. N. Nguyen and P. Tiwari	Brain MRI Image Classification for Cancer Detection Using Deep Wavelet Autoencoder-Based Deep Neural Network	IEEE Access/2019	The performance criterion for the Deep Wavelet Autoencoder-Deep Neural Network classifier was compared with other existing classifiers like Autoencoder-DeepNeuralNetwork or Deep Neural Network

Existing Solution vs Proposed Solution

- Similar medical related problems have been addressed using deep learning and Machine learning.

- System with much better accuracy for detecting the various types of Intracranial bleeding by comparing with two neural networks.

Methodology

- The data is first sorted into 5 categories with a total of approximately 34,000 images.
- With the available images we perform image pre processing techniques like image resizing and RGB to grayscale conversion.
- While resizing of image the image may get stretched so we normalise the image to give proper feed to the model.
- Once the image pre processing techniques are done the CNN model is created and trained with values.
- Over 80% of the entire data is given as input for the training model after which the model is capable of detecting the bleeding and classifying it inti types.
- It can be analysed by testing the model with the rest of 20% of images.

Steps Involved In Image Pre-processing

Reading Images:

We store the path to our image dataset to load them as input .

Resizing:

Some images captured and fed to the algorithm might vary in size . Therefore, we should establish a base size for all images fed into our algorithm.

Noise Removal:

Gaussian blur is used to remove the image noise. Gaussian Blur is used as a pre-processing stage in algorithms for image restoration.

Segmentation & Morphology

In this stage, we segment this image separating the background from foreground objects. At this stage, additional blur is added to further enhance the image.

Data portioning and Validation

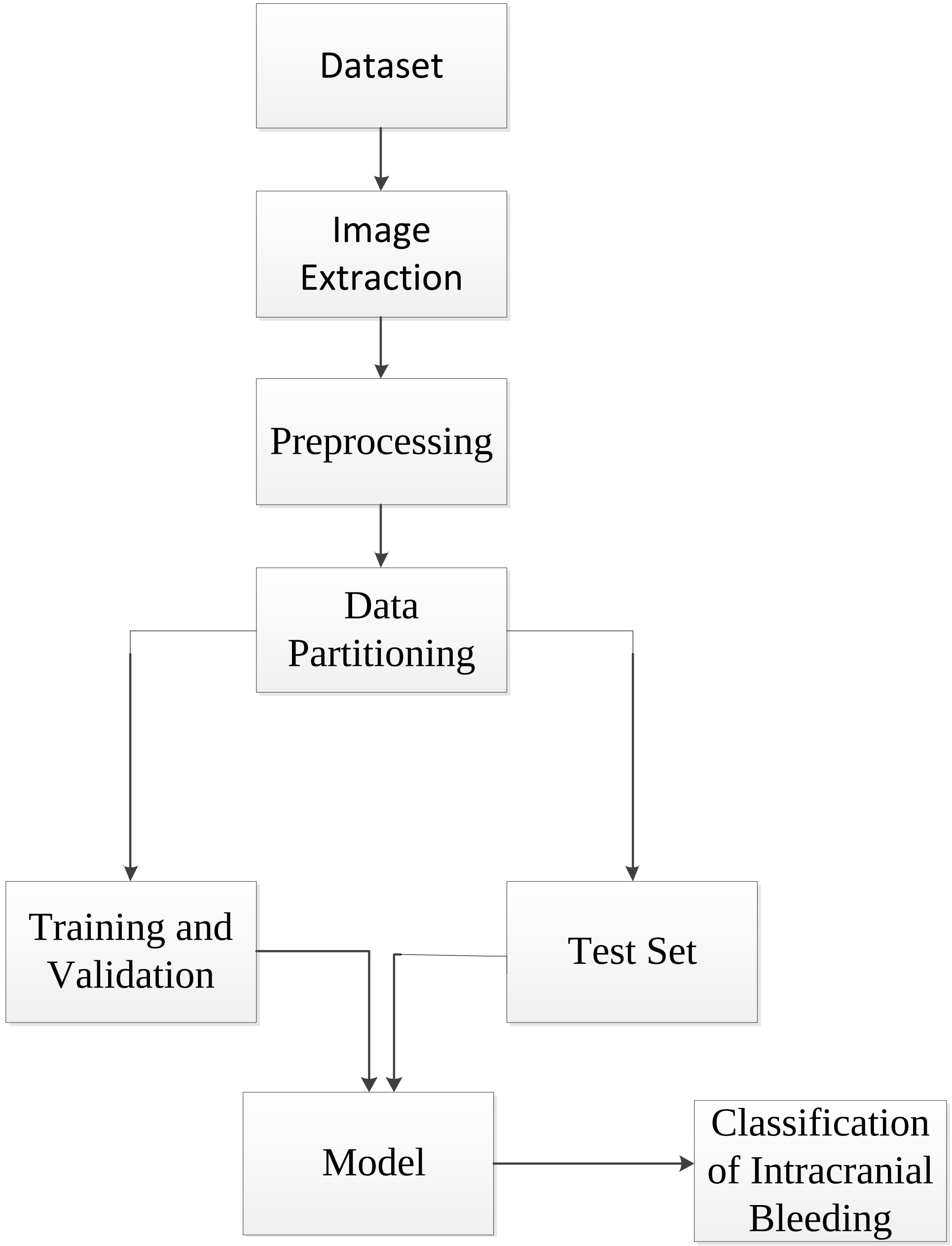
Data Portioning:

In data partitioning we'll get a logical distribution of large data sets in different partitions, which will allow us to make more efficient queries, facilitate the management and improve the maintenance of the system.

Validation:

The training and validation set is used to train the network and the test set is used to check with the final model.

Block Diagram



Tool used [Hardware / Software]

Software used:

Programming platform>Jupyter Notebook

Dataset:

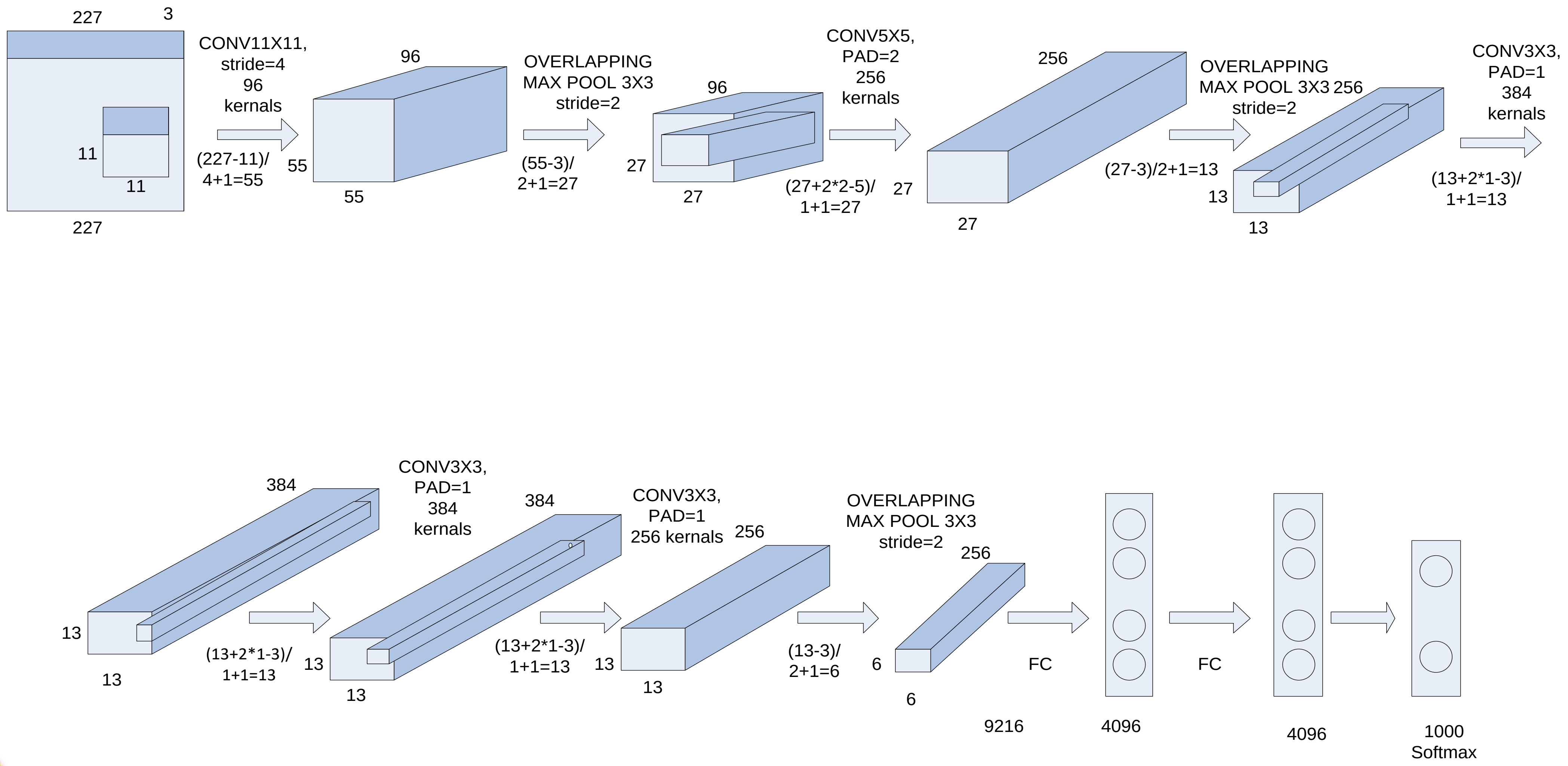
The image dataset obtained from KAGGLE

Image modality : CT scans

DATASET

Image Subclass	No of images
Epidural	5000
Intraventricular	8000
Intraparenchymal	6000
Subdural	8000
Subarachnoid	5000
Total	32000(approx)

ALEXNET



“ Detection of intracranial bleeding using an effective neural network”, Group Name : “kingsmen”

Flow Diagram

Flow Diagram using Alexnet:(visio has some issues sir so temporarily I used this type f drawing sir)

Collection of input dataset from Kaggle

⇩

Preprocessing of the collected dataset

⇩

Preprocessed images are given to chosen neural network(Transfer learning)

⇩

Weight balancing the neural network

⇩

Train the alexnet using preprocessed images

⇩

Save and load the trained alexnet for validation

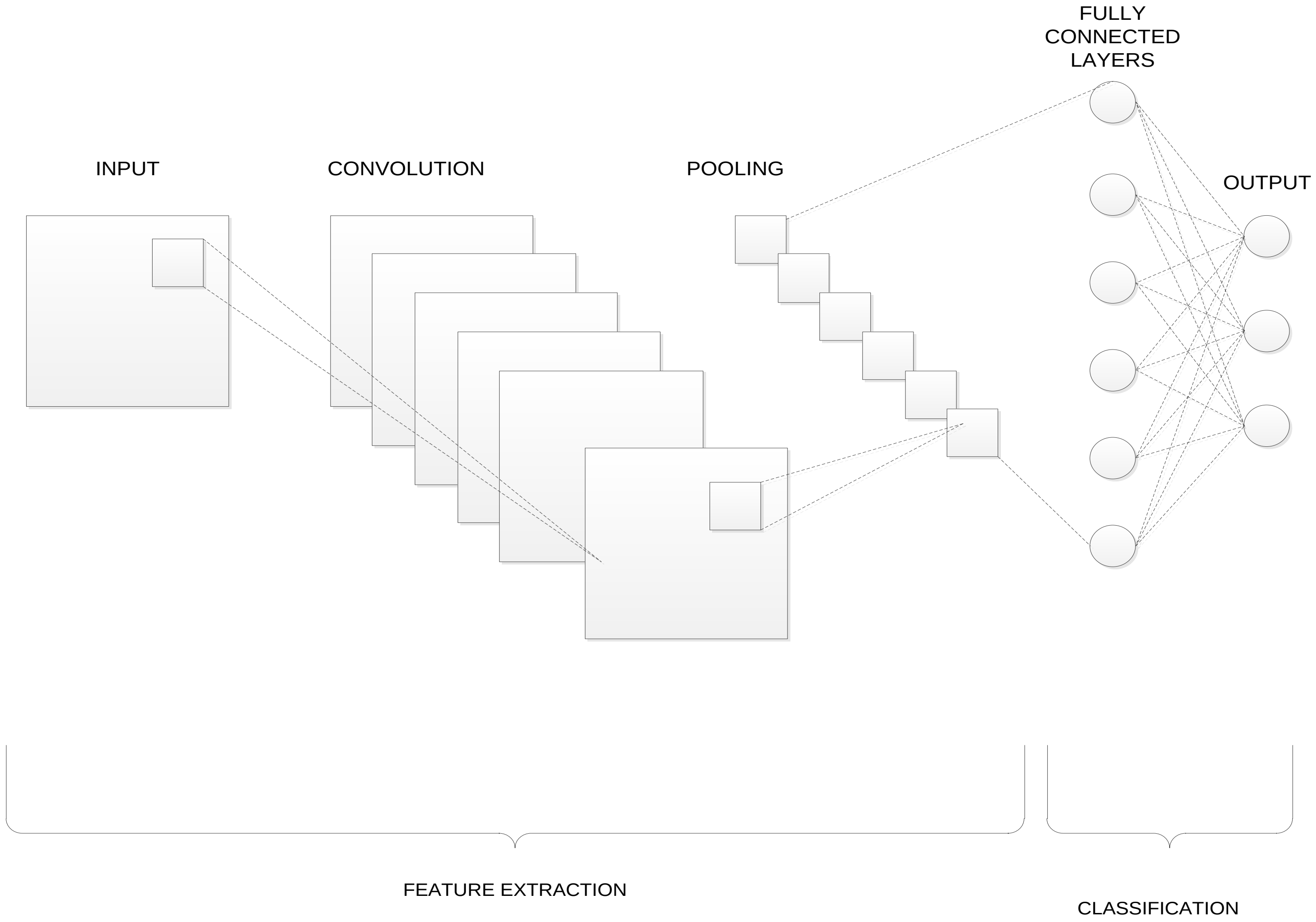
⇩

Sample image given for validation of trained network

⇩

Output is displayed

CNN MODEL


FULLY CONNECTED LAYERS
INPUT
CONVOLUTION
POOLING
OUTPUT
FEATURE EXTRACTION
CLASSIFICATION

Flow Diagram

Flow Diagram using CNN: (visio has some issues sir so temporarily I used this type f drawing sir)

Collection of input dataset from Kaggle

⇩

Preprocessing of the collected dataset

⇩

Preprocessed images are given to chosen neural network(Modified CNN)

⇩

Weight balancing the neural network

⇩

Train the CNN using preprocessed images

⇩

Save and load the trained CNN for validation

⇩

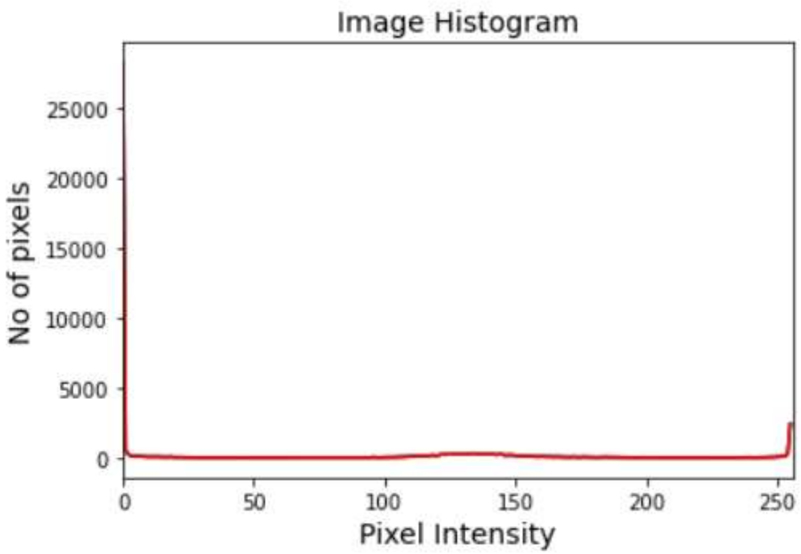
Sample image given for validation of trained network

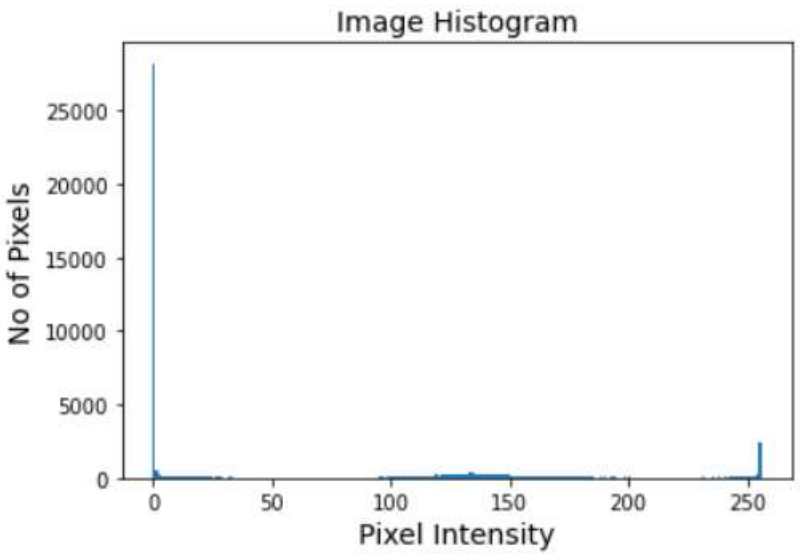
⇩

Output is displayed

Work done & Results

Image Analysis:





Work done & Results

Weight Balancing

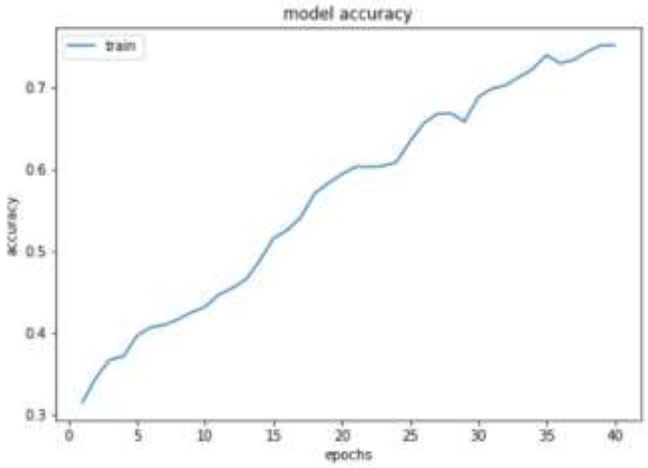
```
In [12]:  model.compile(optimizer=optimzier, loss=BinaryFocalLoss(gamma=2),
                        metrics=['accuracy'])
```

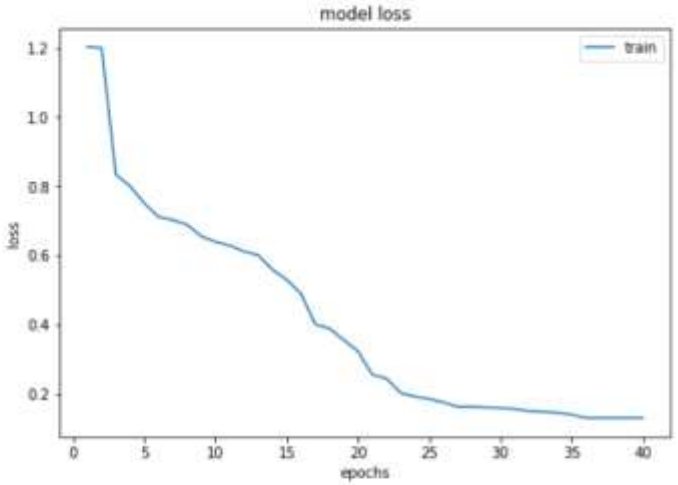
Binary focal loss function generalizes binary cross-entropy by introducing a hyperparameter called the focusing parameter that allows hard-to-classify examples to be penalized more heavily relative to easy-to-classify examples.

Work done & Results

Accuracy using Alexnet (Train Set)

Epoch : 100
Batch size: 35
Loss : 42.37%
Accuracy : 75.10%



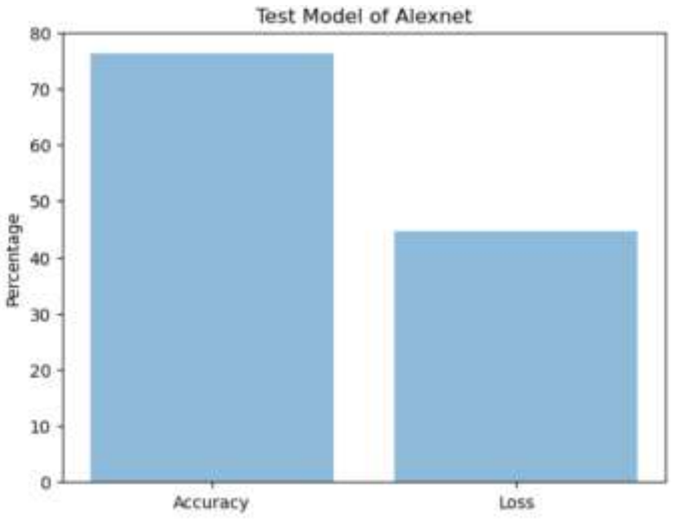


Work done & Results

Accuracy using Alexnet (Test Set)

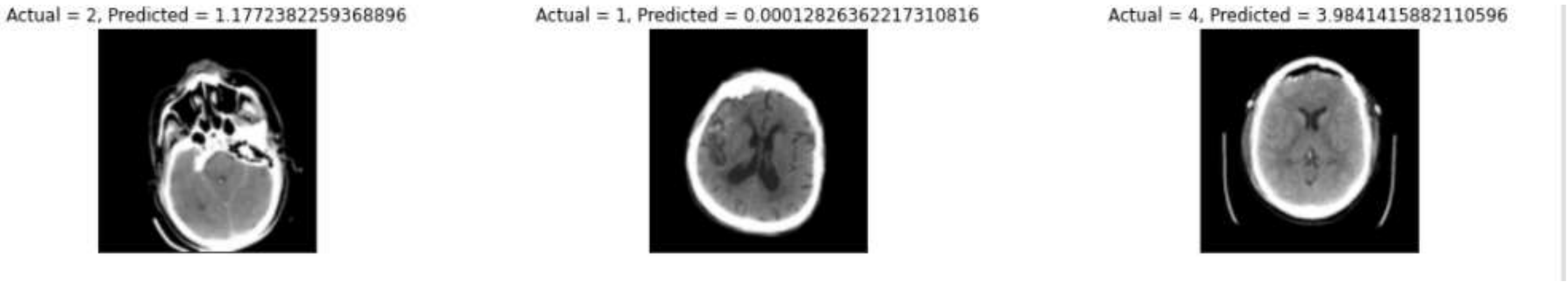
Loss : 55.60%
Accuracy : 76.21%

```
In [16]: loss, accuracy = model.evaluate(x_test, y_test)

         print(loss,accuracy)

872/872 [==============================] - 384s 441ms/step - loss: 0.5560 - accuracy: 0.7621
0.5560425519943237 0.7621472477912903
```



OUTPUT

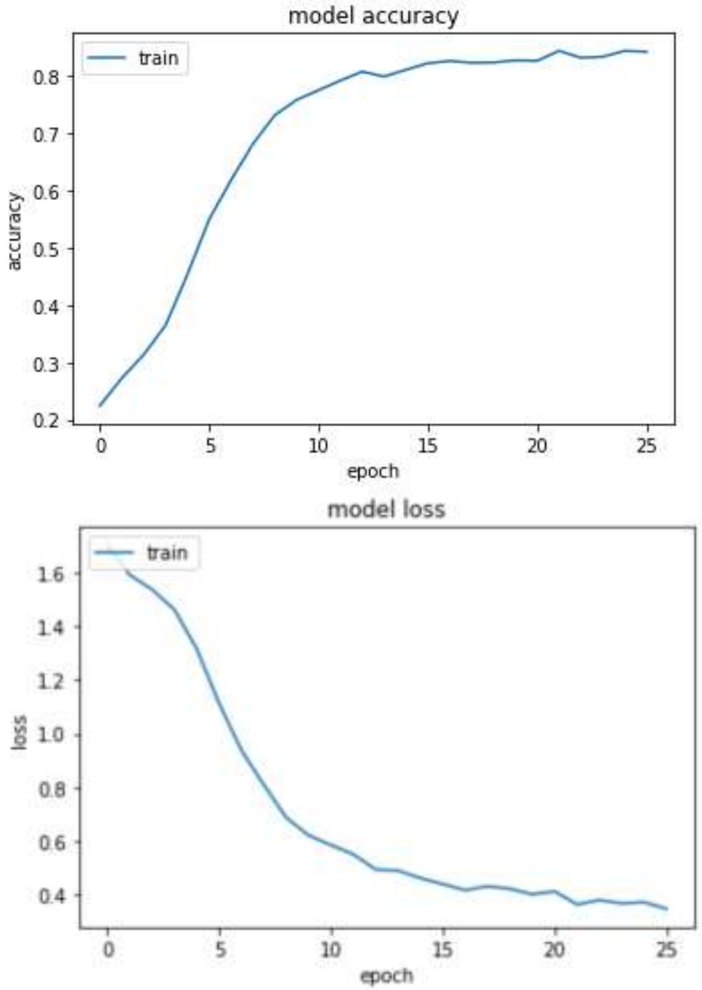
Predicted Output using Alexnet



Work done & Results

Accuracy using modified CNN(Train)

Epochs: 20
Batch size: 35
Loss: 41.92%
Accuracy:82.00%

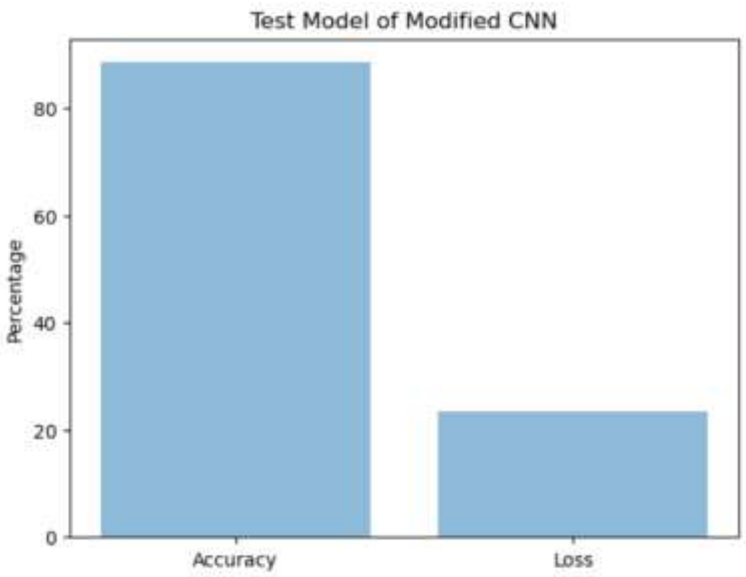


Work done & Results

Accuracy using Modified CNN (Test Set)

Loss: 26.10%
Accuracy: 88.45%

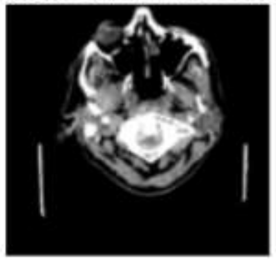
```
In [15]: loss, accuracy = model.evaluate(x_test, y_test)
         print(loss,accuracy)

100/100 [==============================] - 57s 572ms/step - loss: 0.2610 - accuracy: 0.8845
0.26096630096435547 0.8845185637474060
```



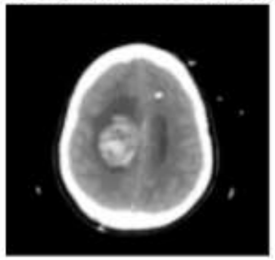
OUTPUT

Predicted Output using Modified CNN

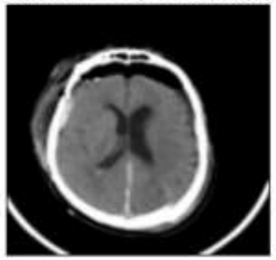
Actual = 3, Predicted = 3.0



Actual = 2, Predicted = 1.1185382604599



Actual = 2, Predicted = 1.4278862181527074e-05



Roles & Responsibilities

Student Name	Contribution
Teressa Alphonsa Dominic	Concepts, Literature Survey, Paper, PPT, Code, Debugging, Thesis
Karthikeyan	Concepts, Literature Survey, Paper, PPT, Code, Debugging, Thesis
Sanjay Roy	Concepts, Literature Survey, Paper, PPT, Code, Debugging, Thesis
Suriya kumar	Concepts, Literature Survey, Paper, PPT, Code, Debugging, Thesis

Work Plan

Month / Week	Plan
Dec / (1 - 2)	Literature Survey / Zeroth Review / Project Approval
Dec / (3 - 4)	Basic concepts / Dataset collection / Code
Jan / (1 - 2)	CNN / Analyzing the code
Jan / (3 - 4)	Debugging
Feb / (3 - 4)	AlexNet / Debugging / optimizing code for accuracy
Mar / (1-2)	Enhancing AlexNet code / Work on paper
Mar / (3-4)	To use other DL architectures / Work on paper
Apr / (1-2)	Work on paper / Thesis
Apr / (1-2)	Project & Paper submission

Conclusion

Detection of Intracranial bleed at their early stage increases the survival rate of patients. The main reason for many dying of this Intracranial bleeding is because doctors can not diagnose this at a early stage The proposed system will help doctors to find the bleed at early stage.

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Thank You