ACUTE INTRACRANIAL HEMORRHAGE DETECTION USING CNN & RNN

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ABSTRACT:-

Computed tomography (CT) of the head is utilized worldwide to analyze neurologic crises. Brain hemorrhage is a severe threat to human life, and its timely and correct diagnosis and treatment are of great importance.Multiple types of brain hemorrhage are distinguished depending on the location and character of bleeding. The main division covers five subtypes:subdural, epidural,intracranial,intraparenchymal, and subarachnoid hemorrhage.This project presents an approach to detect these intracranial hemorrhage types in computedtomography(CT)images of the head.To detect the type of hemorrhages we are using hybrid deep learning model that is combination of convolution neural network and recurrent neural network (CNN-RNN) .A CNN-RNN deep learning framework was developed for ICH detection and subtype classification and this deep learning framework is fast and accurate at detecting ICH and its subtypes.

Keywords—CT scans, Hemmorhage, deep learning, convolutional neural network.

I. INTRODUCTION

Intracranial Hemorrhage (IH) happens when an infected vein inside the mind explodes, permitting blood to leak inside the cerebrum. The abrupt expansion in pressure inside the cerebrum can make harm the mind cells surrounding the blood. Fast expansion in blood sum may cause unexpected development in pressure which thusly canlead to obviousness or passing. IH may stretch out into ventricles in relationship with profound, huge hematomas.Intracranial drain generally happens in chosen portions of the mind, including the basal ganglia, cerebellum,brain stem, or cortex. Intracranial discharge represents 10 to 15 percent of all instances of stroke and is related with the most noteworthy death rate, with just 38% of affected patients enduring the initial year.1, 2IH can be ordered into intra pivotal and extra hub drain dependent on draining inside or outside the cerebrum substance. Intra hub drain can be further classified into cerebral discharge, and intraventricular discharge (IVH) in view of the specific anatomical area of dying. Additional crucial discharge is classified as per the anatomical layer of meninges where draining happens, specifically extra dural drain (EDH),subdural drain (SDH), subarachnoid discharge (SAH).In moderate to serious head injury cases, non-contrast-improved CT examining is the most valuable and preferredchoice for starting imaging method.

Explanations for this decision is CT examines being fast and its capacity to identify intense discharge, cerebral growing, proof of raised intracranial pressing factor and pneumocephalus. New intracerebral blood ordinarily seems hyperdense on CT because of the great protein focus and its high mass thickness. Nonetheless, periodically intense intracerebral hematoma can seem is odense or even hypodense on CT.

CT examining can show the size and area of the Intracranial Hemorrhage precisely. Likewise it can recommend potential causes like tumor, vascular abnormality, or aneurysm.1Since recent years, PC helped finding (CAD) has gotten one of the significant exploration regions in clinical imaging and symptomatic radiology. The fundamental idea of CAD is to give a PC yield as a subsequent assessment to help radiologist's picture readings. The objective of CAD is to improve the quality and usefulness of radiologist's

II. RELATEDWORK

Nguyen et al. presented a comprehensive analysis of state-of-the-art on recent development andchallengesof human detection

For visual recognition, techniques using deep convolutional neural network (CNN) have beenshown to achievesuperior performanceon manyimagerecognition benchmarks .

Different CNN models for object detection with its object localization had been proposed interms of network architecture, algorithms, and new ideas. In recent years, CNN models such asAlexNet

Hence, the real-time algorithms of object detection using the CNN model such as R-CNNandYOLO

III. METHODOLOGY

In the Machine Learning(ML) stage the component-rich pictures are feed into the preparation set. For the execution reason, we have utilized the Keras library in python to run the ML calculation. ML is enlivened by the working of the cerebrum. The entire model comprises of layers, very much like neurons in the cerebrum. This model learns by thinking about models. The consecutive model is made utilizing Keras. At first two layers are added with a rectifier work. The subsequent stage is adding a pooling layer of 2x2 framework. Presently the pooled pictures are changed over into a consistent vector.

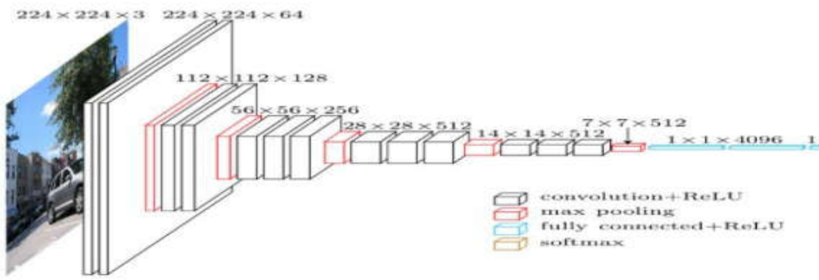
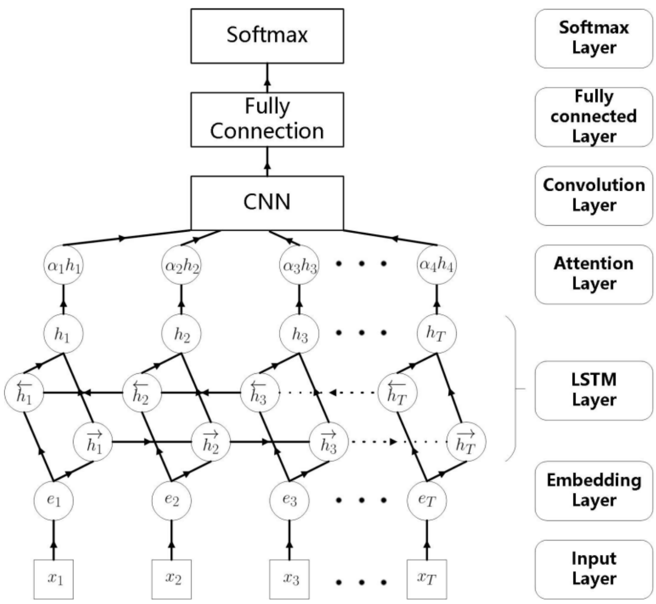


Fig. Downsampling

<u>PIPELINEOFTHE PROJECT</u>



The secret layer is currently added, this layer will contain every one of the hubs, called counterfeit neurons. These layers mimic the human mind by learning layers by layers. When every one of the layers are added, the model is incorporated and saved as an h5 document which can be stacked toward the front so we don't need to prepare the model without fail.

IV.IMPLEMENTATION

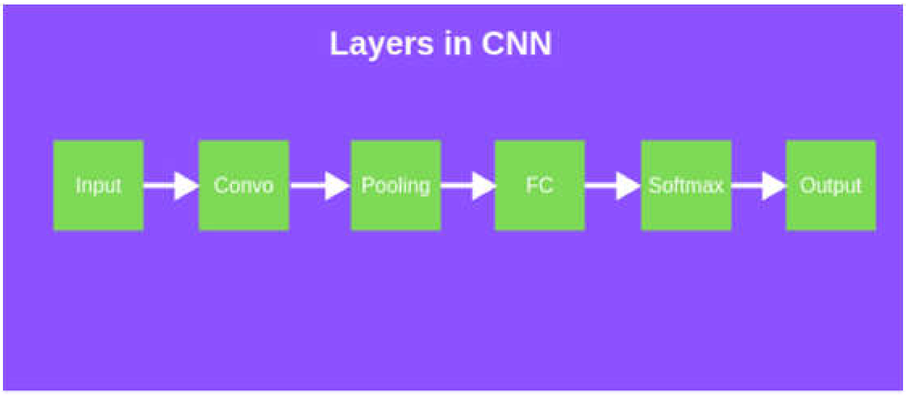
The information gathered comprises of around 1470 records and 35 characteristics and target property that is Attrition of a worker. To anticipate the wearing down of a worker we need to assemble an ML model. For that we have utilized the Jupyter Notebook and IBM cloud for preparing the model and conveying it. Building an ML incorporates the accompanying advances.

- DataPreprocessing
- FeatureExtraction
- ModelTraining
- Prediction
- Deployment toPrediction

Data Preprocessing:

There are five different layers in CNN

- Inputlayer
- Convo layer (Convo +ReLU)
- Pooling Layer
- LSTM layer
- Fully Connected (FC) Layer
- Outputlayer



Input Layer:

The information layer in CNN ought to contain picture information. Picture information is addressed by three-dimensional grid as we saw before. You need to reshape it's anything but a solitary section. Assume you have a picture of measurement 28 x 28 =784, you need to change over it to 784 x 1 preceding taking care of it into input. In the event that you have "m" preparing models measurement of information will be (784, m).

Convo Layer:

Convo layer is at times called Feature extractor layer since highlights of the picture are get removed inside this layer. Most importantly, a piece of picture is associated with Convo layer to perform convolution activity as we saw before and ascertaining the spot item between responsive field(it is a nearby district of the information picture that has the very size as that of channel) and the channel. Consequence of the activity is single whole number of the yield volume. Then, at that point we slide the channel over the course of the following open field of a similar information picture by a Stride and do a similar activity once more. We will rehash a similar cycle and again until we go through the entire picture. The yield will be the contribution for the following layer

Pooling Layer:

Pooling layer is utilized to diminish the spatial volume of information picture after convolution. It is utilized between two convolution layer. In the event that we apply FC after Convo layer without applying pooling or max pooling, then, at that point it will be computationally costly and we don't need it. Thus, the maximum pooling is best way to diminish the spatial volume of info picture. In the above model, we have applied max pooling in single profundity cut with Stride of 2. You can notice the 4 x 4 measurement input is decrease to 2 x 2 measurement.

There is no boundary in pooling layer except for it has two hyperparameters — Filter(F) and Stride(S).

All in all, on the off chance that we have input measurement W1 x H1 x D1,

W2 = (W1−F)/S+1

H2 = (H1−F)/S+1

D2 = D1

Where W2, H2 and D2 are the width, Length and profundity of output.

LSTM Layer:

Long short-term memory (**LSTM**) is an artificial recurrent neural network (**RNN**) architecture used in the field of deep learning. **LSTM** networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series.

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Fully Connected Layer(FC):

Fully Connected Layer includes loads, inclinations, and neurons. It associates neurons in a single layer to neurons in another layer. It is utilized to group pictures between various class via preparing.

Softmax/Logistic Layer:

Softmax or Logistic layer is the last layer of CNN. It dwells toward the finish of FC layer. Calculated is utilized for parallel order and softmax is for multi-arrangement.

Output Layer:
Output layer contains the name which is as one-hot encoded. connected layer involves weights, biases, and neurons. It connects neurons in one layer to neurons in another layer. It is used to classify images between different category by training.

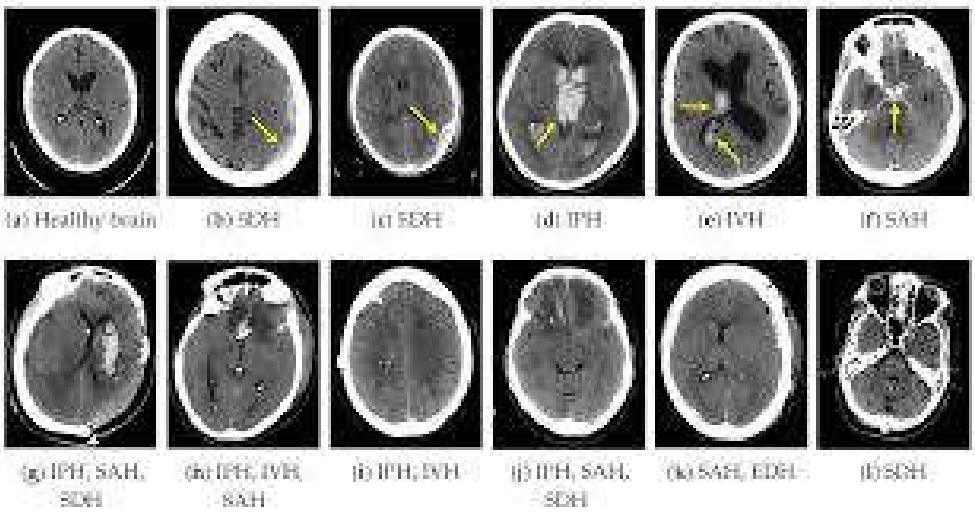
Softmax / Logistic Layer:

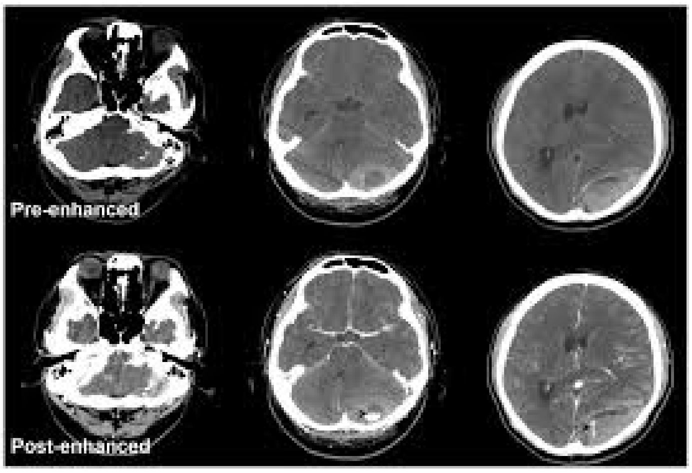
Softmax or Logistic layer is the last layer of CNN. It resides at the end of FC layer. Logistic is used for binary classification and softmax is for multi-classification.

Output Layer:
Output layer contains the label which is in the form of one-hot encoded.

Data Preparation:
High-quality data has always been the primary requirement of learning reliable algorithms. Particularly, training a deep neural network requires large amount of labeled data. Therefore, high-quality skin disease data with reliable diagnoses is significant for the development of advanced algorithms. Three major types of modalities are utilized for skin disease diagnosis, i.e., clinical images, dermoscopy images and pathological images.Specifically, clinical images of skin lesions areusually captured with mobile cameras for remote examination taken as medical records for patients.
Dermoscopy images are obtained with high-resolution digital single-lens reflex (DSLR) or smart phone camera attachments. Pathological images, captured by scanning a tissue slide with a microscope and digitalized as an image, are served as a gold standard for skin disease diagnosis. Recently, many public datasets for skin disease diagnosis tasks have started to emerge.
There exists growing trend in the research community to list these datasets for reference. In the following, we present several publicly available datasets for skin disease.

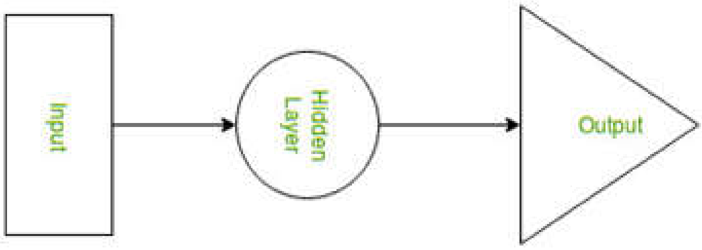
Hemorrhage images:





Recurrent Neural Network(RNN):

Recurrent Neural Network(RNN) are a type of Neural Network where the output from previous step are fed as input to the current step. In traditional neural networks, all the inputs and outputs are independent of each other, but in cases like when it is required to predict the next word of a sentence, the previous words are required and hence there is a need to remember the previous words. RNN came into the occurrence, which resolved this issue with the aid of a Hidden Layer. The main and most prominent feature of RNN is Hidden state, which remembers some information about a sequence



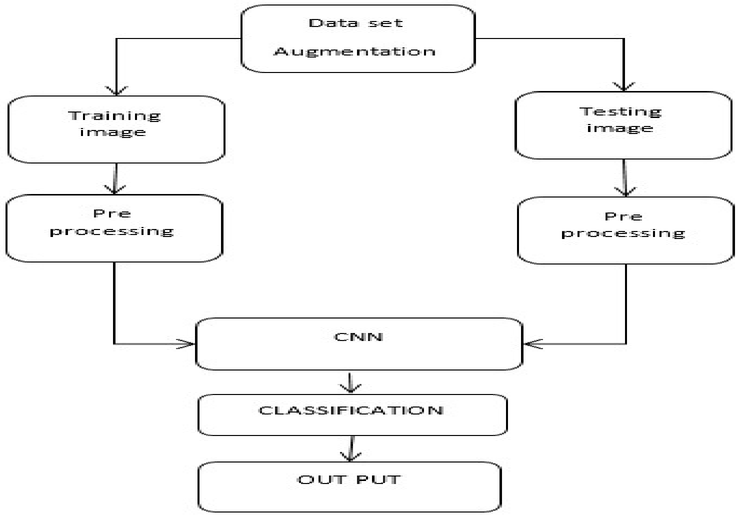
RNN have a "memory" which recalls all data about what has been determined. It utilizes similar boundaries for each contribution as it plays out similar undertaking on every one of the sources of info or covered up layers to create the yield. This decreases the intricacy of boundaries, in contrast to other neural organizations

V. RESULT AND DISCUSSION

Accuracy Score:

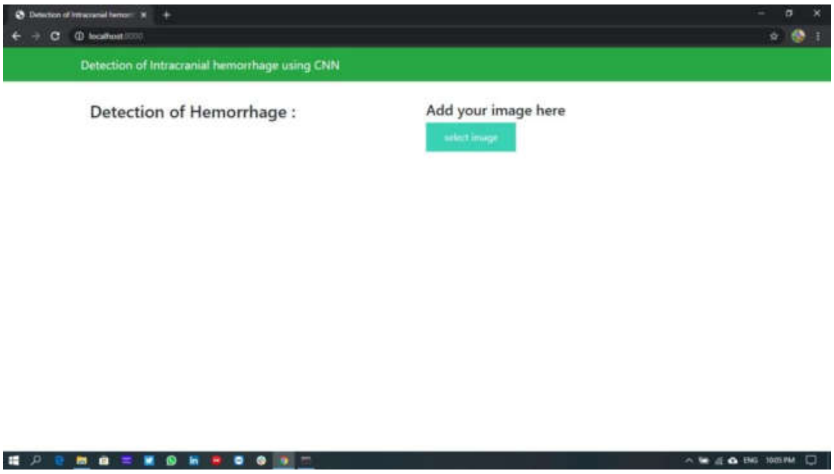
The accuracy can be termed as closeness of measurements in statistical measures, however it is also used in classifications. In classifications accuracy is the proportion of true results among the total number of cases. And to our model we got an accuracy of about 85% which indicates a good classification accuracy rate.

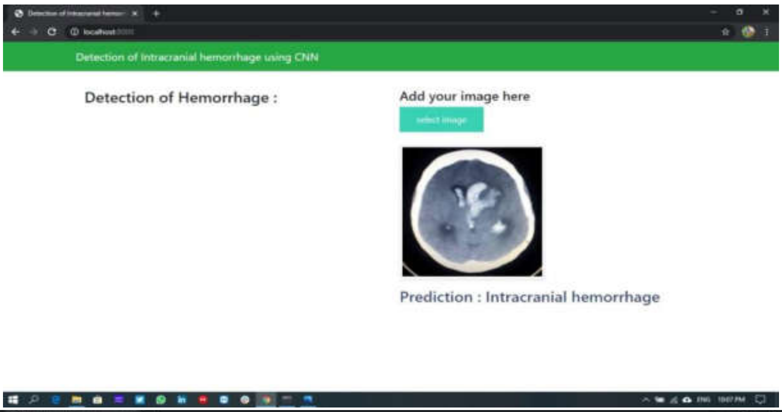
Skin problem is growing fast all over the country. It is one of the most common types of diseases where some can be painful and some can cause fatal to human life. Everyone should pay attention towards this alarming and emerging health problem which is spreading fast due to numerous reasons like global warming . To avoid delay in treatment, we have developed a model which will classify the disease using image dataset. The model uses the deep learning approach to get trained for classification. It works on Convolutional Neural Network (CNN) and Recurrent NeuralNetwork(RNN)

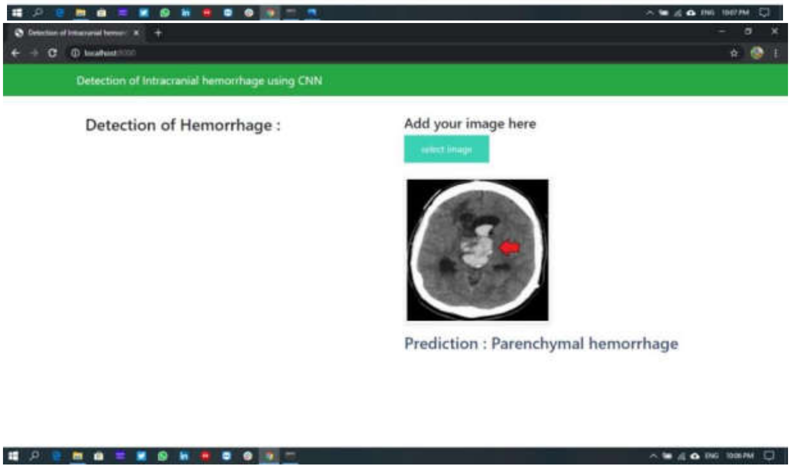

Data set
Augmentation
Training image
Testing image
Pre processing
Pre processing
CNN
CLASSIFICATION
OUT PUT

VI.CONCLUSION

The present study investigated a method to identify the Intracranial Hemorrhage using Deeplearningalgorithm(CNN+RNN)on the image.







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VII. FUTUREWORK

For future work we propose a way in which the image can be uploaded in an android or ios application and the type of hemorrhage can be detected easily by the person or doctor himself.

This can be help full for easier analysis of CT scans

VIII. REFERENCES

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