DEEP LEARNING BASED BRAIN STROKE DETECTION

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ABSTRACT: Machine learning has been used to evaluate medical data sets for decades. One of the most common ailments among the elderly is stroke. The representation approach of these images is often used to diagnose stroke early. Deep learning technology has recently gained traction in a variety of fields, including computer vision, image identification, natural language processing, and, most notably, radiography. Using CNN and deep learning models, this study seeks to diagnose brain stroke images. The suggested method uses a Convolutional neural network to classify brain stroke images into normal and pathological categories. The best algorithm for all classification processes is the convolutional neural network. We discovered that deep learning models are not only useful for non-medical images but also provide accurate results in medical image diagnostics, particularly in the detection of brain stroke.

KEYWORDS: Stroke detection, Computer vision, Image recognition, Deep learning, CNN

1. INTRODUCTION

Deep learning is a type of machine learning that teaches computers to mimic human behaviour. It is also known as deep structured learning and is part of a larger family of machine learning approaches based on representation learning and artificial neural networks. The majority of modern deep learning models are built on artificial neural networks, notably convolutional neural networks (CNNs), though they can also include propositional formulas or latent variables structured layer-wise in deep generative models like nodes in deep belief networks. So that by using CNN method it is possible to achieve the most accurate method of detecting brain stroke. With earliest detection of stroke, it is possible to treat the stroke and to reduce death rate.

2. PROPOSED METHOD

Deep Learning is a subset of Machine Learning that uses algorithms to process data and construct abstractions or replicate the thinking process. Deep Learning (DL) uses layered algorithms to process data, recognise human speech, and visually assess objects. Each layer sends data to the next, with the output of the previous layer serving as input to the next. In a network, the input layer is the first and the output layer is the last. The layers that exist between the two are known as hidden layers. Typically, each layer is a simple, uniform algorithm with only one type of activation function.

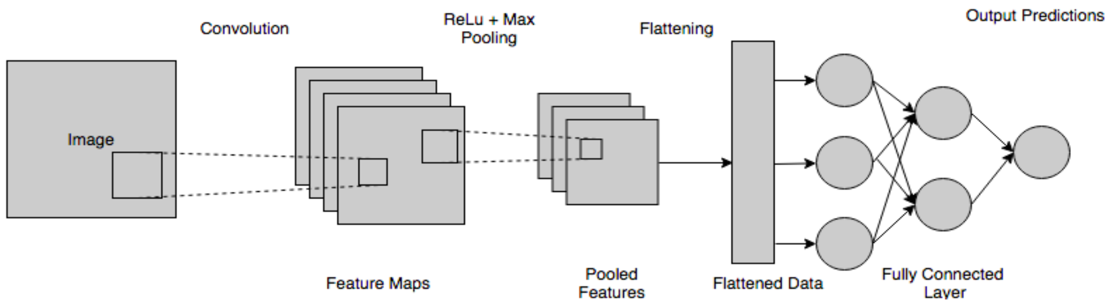
A Convolutional Neural Network is a Deep Learning system that can take in an image as input, assign priority to various aspects/objects in the image, and differentiate between them. CNN apparently uses four layers:

1. Convolution layer

2.Pooling layer

3.Flattern layer

4.Fully connected layer



Fig,2.1 Convolutional Neural Network

2.1 CONVOLUTION LAYER

The input image is transformed using a convolution layer in order to extract features from it. The picture is convolved with a kernel in this transformation. A kernel is a tiny matrix that is smaller in height and width than the image to be convolved. A convolution matrix or convolution mask is another name for it.

The cornerstone of a CNN is the convolutional layer, which houses the majority of the computation. It requires, among other things, input data, a filter, and a feature map. Assume the input is a colour image made up of a 3D pixel matrix. This means that the input will have three dimensions, which match to the RGB colour space of a picture. A feature detector, also called a kernel or a filter, will scan the image's receptive fields for the presence of the feature. This method is known as convolution.

In the feature detector, a two-dimensional (2-D) array of weights represents a portion of the image. The size of the receptive field is also affected by the filter size, which can vary in size. After applying the filter to a section of the image, the dot product of the input pixels and the filter is calculated. The output array is then filled with the dot product. The kernel is then swept across the entire image by shifting the filter by a stride. The ultimate result of a succession of dot products from the input and the filter is a feature map, activation map, or convolved feature.

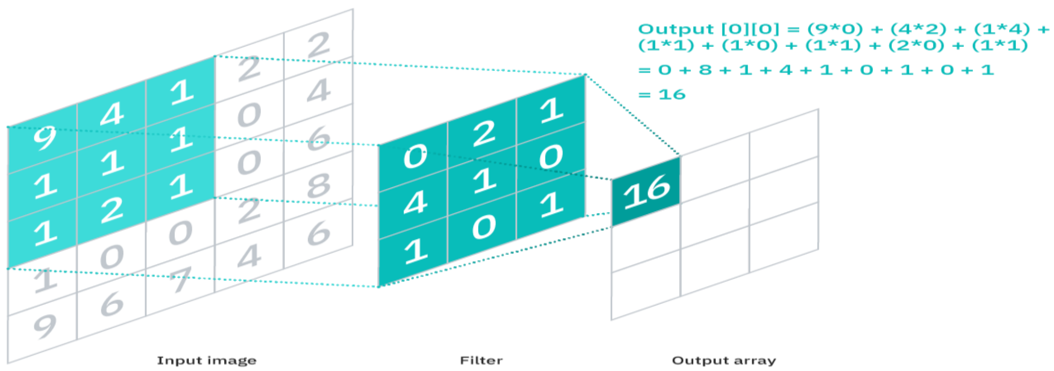


Fig.2.2 Convolutional Layer

2.2.POOLING LAYER

Pooling layers, also known as downsampling, is a dimensionality reduction technique that minimises the number of components in the input. Similar to the convolutional layer, the pooling method sweeps a filter across the entire input, but this filter has no weights. Instead, the kernel populates the output array with values from the receptive field using an aggregation function.

There are two main types of pooling:

Max pooling:

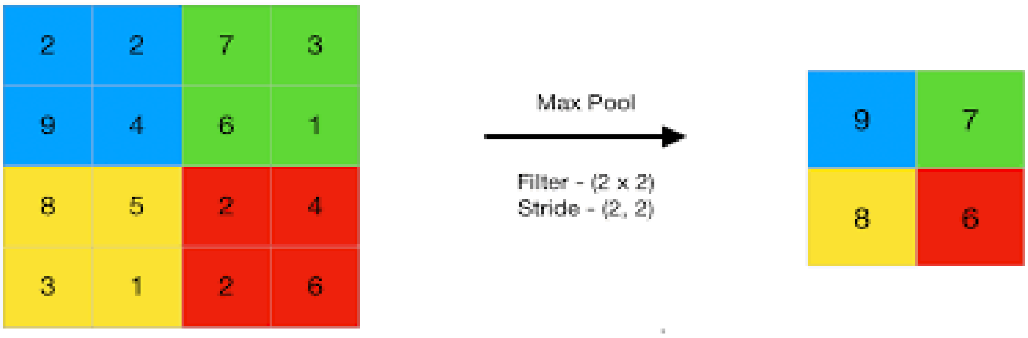
The filter selects the pixel with the highest value to transmit to the output array as it advances across the input. In comparison to average pooling, this strategy is employed more frequently.

Average pooling:

As the filter passes over the input, the average value inside the receptive field is calculated and transferred to the output array.

While the pooling layer loses a lot of information, it does provide some advantages for CNN. They assist in reducing complexity, increasing efficiency, and reducing the risk of overfitting.

Max Pooling is a type of convolution in which the Kernel collects the maximum value from the area it convolves. Max Pooling basically tells the Convolutional Neural Network that just that information will be carried forward if it is the most amplitude-wise accessible.



Fig,2.3 Pooling layer

2.3.FLATTERN LAYER

The flatten function lowers multi-dimensional input tensors to a single dimension, allowing you to model your input layer and design your neural network model, then feed those inputs to each and every neuron properly.

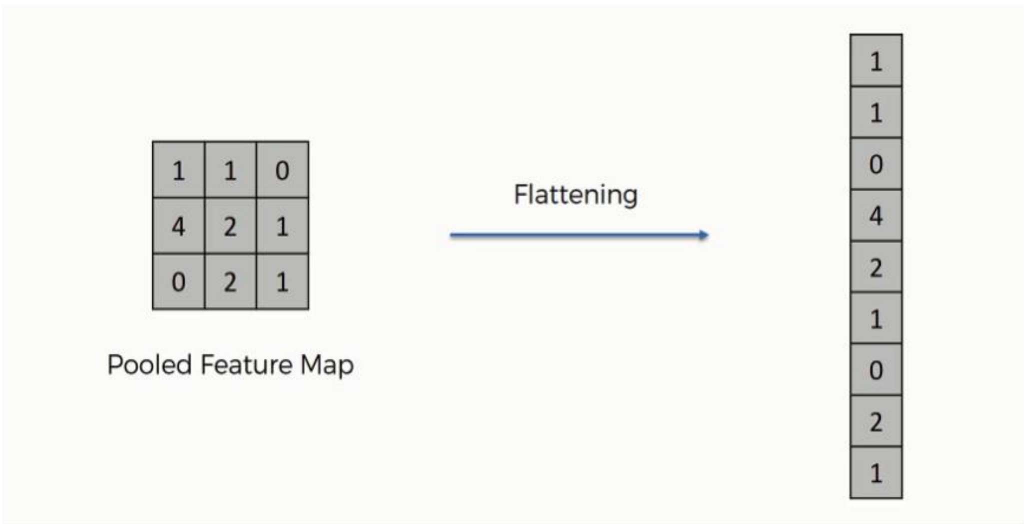


Fig.2.4 Flattern layer

2.4.FULLY CONNECTED LAYER

The name of the fully-connected layer is self-explanatory. The pixel values of the input image are not directly related to the output layer in partially linked layers, as previously indicated. In the fully-connected layer, each node in the output layer connects directly to a node in the previous layer. This layer performs classification tasks using the features and filters retrieved by the preceding levels. While convolutional and pooling layers utilise ReLu functions to categorise inputs, FC layers use a softmax activation function to generate a probability from 0 to 1.

Each neuron in a fully connected layer is linked to every neuron in the previous layer, and each link has its own weight. This is a completely generic connection pattern that makes no assumptions about the data's characteristics.

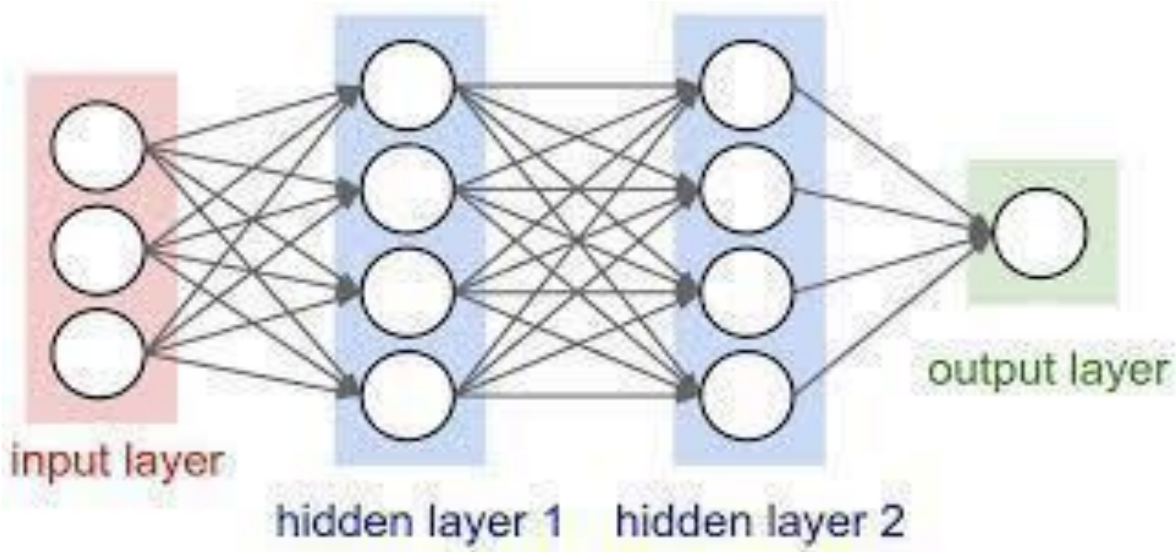


Fig.2.5 Fully connected layer

2.5.SOFTWARE

The software employed in the proposed includes Windows 10 OS,Python language,Python IDLE platform and libraries such as Keras,Open CV, Pickle and also packages such as Matplotlib,Scikit learn,numpy,imultis and frameworks includes tensorflow and Tkinter.

3.ADVANTAGES

- CNN takes essential features into account automatically.
- High precision.
- CNN's Working Process is quite fast.
- Large data sets are best suited.

4.TRAINING MODEL

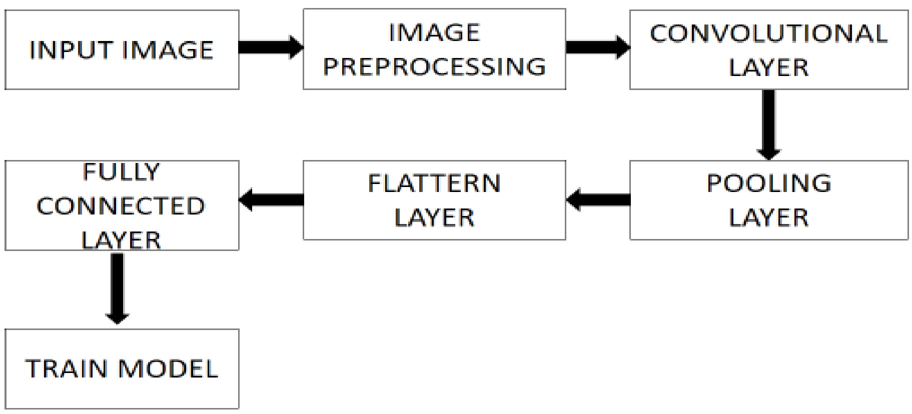


Fig.4.1 Training model

5.TESTING MODEL

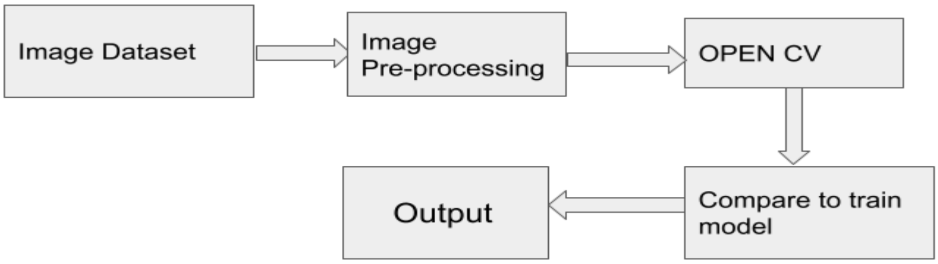


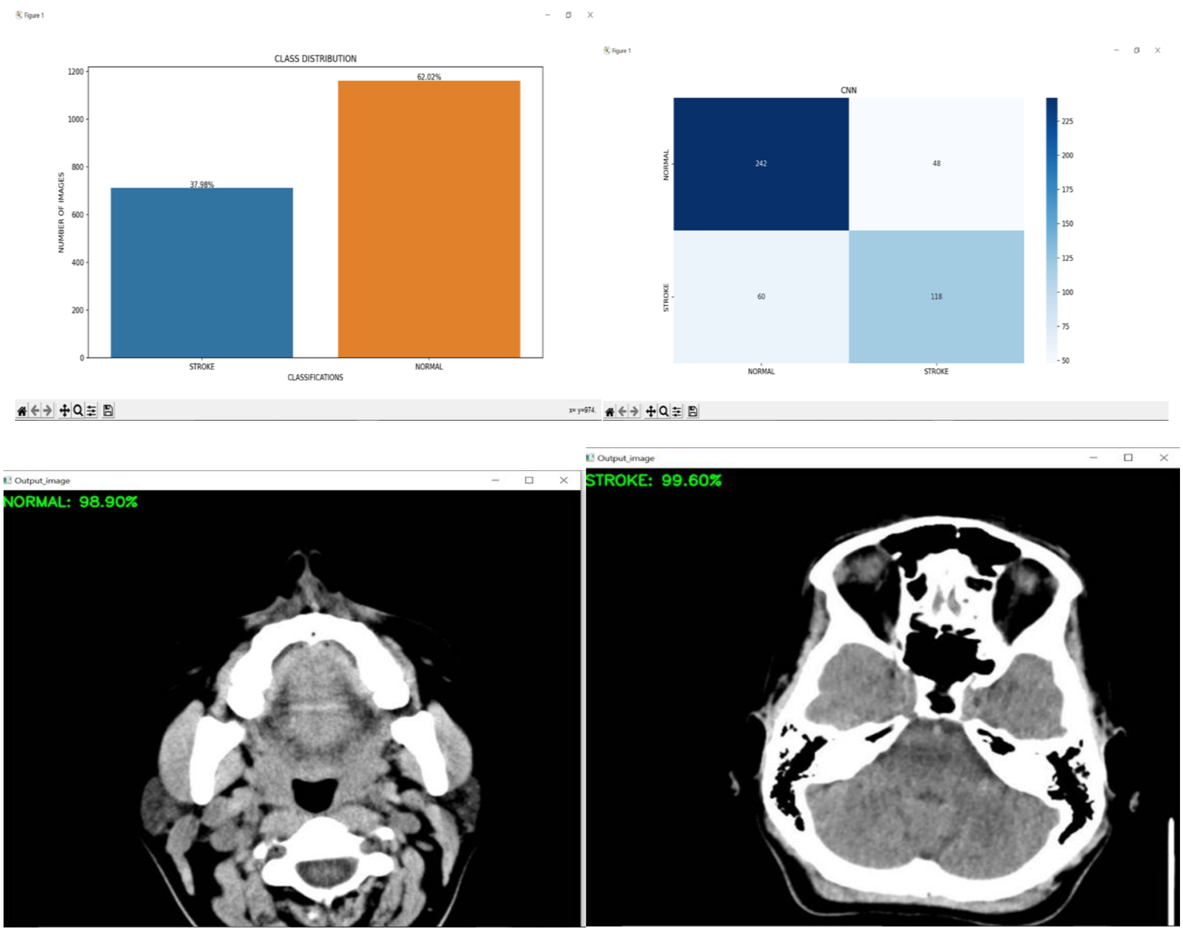
Fig.5.1 Testing model

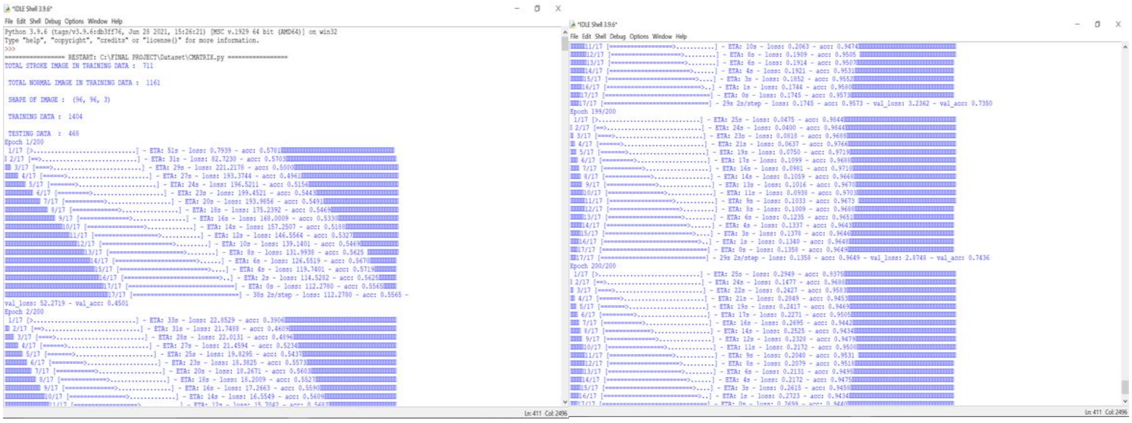
6.CONCLUSION

The project's major goal is to detect a stroke in the brain in advance with the highest level of accuracy. This will aid in lowering the death rate from brain stroke. The most traumatic one is a stroke of the brain. For classification, the suggested system employs a Convolutional Neural Network.This project can be carried out by developing a website where anyone can submit a CT brain image for classification. For the same dataset classification, different Machine Learning Algorithms can be employed.

RESULT

The proposed system accurately diagnoses the incidence of a haemorrhage in the human brain by utilising CT scan images, and the output is successfully achieved.





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