Optimal Technique of Tumor Detection and Prediction of Livestock by Deep Neural Network with TensorFlow and Keras

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Abstract – In this paper, we emphasis on the method by which a sick livestock can be diagnosed of the probable infections and predict the type of disease. Proposed an approach to distinguish whether an MRI picture of a brain contains a possible tumor of livestock. Designed a computer-aided detection approach to detect a brain tumor in its early stage by using deep neural network using Keras and Tensorflow. The main problem faced by a farmer/livestock owner is that the geographical distances of the sick animal from the healthcenter or the doctors who can treat and suggest the possible cure. By leveraging the modern technology in application and developments in Machine Learning and IOT technology the above-mentioned problem can be addressed as of the optimal approach for the farmer. The Detection of tumor is first predicted by Convolution Neural Network based Deep neural network using Keras and Tensorflow, followed is by which the MRI image is pre-processed to isolate the noise and any artefacts. The results are carried out by proposed method which can communicate directly to the cattle farmer using IOT. However the resultant of the computer aided process will automate the detection of diseases by which the farmers can directly know whether the cattle got effected with tumor or not. Time complexity can be significantly reduced with the proposed method. Eventually, computer aided system will assist the radiologist and the doctor in concluding of any illness on the livestock.

Keyword: Deep Neural Network, IOT, Keras Livestock, Morphological Operation, Tensorflow.

1. Introduction
Livestock play major role in everyday human life they not only provide animal fat and protein for improved nutrition, animals were since ages domesticated to provide the milk; animals skin is helpful in providing leather and wool for clothing and shelter, dried manure from large livestock is fuel for cooking and heating. The major source of the food for us is from the livestock which namely include milk, eggs, cheese, butter, yogurt etc. Nowadays these livestock are confined in a small area
and over exploited by use of medications for extra production of milk or meat, these is affecting them by many diseases. Among these diseases some gives rise to dangerous cancer cells in their body parts particularly in brain. Though it is very rare, the problem is getting severe. A poultry farmer who is unable to detect this at an earlier stage, is losing the life of the animal and thereby his livelihood. So, it has become a major requirement to monitor the cattle regularly. The monitoring of livestock is not simple as the parameters collected has to be collated to get a meaningful conclusions of the alignments, in In this work, we have mainly targeted the tumor diagnosing and in line that approach have collected many of MRI images of livestock brain and detecting the tumor in it by applying CNN (Convulsion Neural Networks) Machine learning techniques. The MRI images are a first source of diagnose but these MRI images contain noise and artifacts, so these must be removed from the image. First, the image is pre-processed to remove the noise. Post processing of the image of noise, we next proceed with the CNN machine learning techniques using Keras and TensorFlow. Brain tumor detection includes the way toward running the automation for differentiation between the healthy and diseased sample. The MRI images are fed to Machine learning models. After few samples of healthy and diseased MRI samples with the CNN model will determine the tumor and then we apply the segmentation to extract the tumor. Thereby we will determine the exact scenario of the tumor detection by comparing with different segmentation algorithms. the additional proposal in our paper is that the automation of the whole process of the related data will be processed quickly and will be sent to the farmers mail with the possible results for conclusion. Here the advantage through our paper is that radiologists will get a possible prediction of the disease and the outline information of tumor as well as intimating the farmer of possible diagnose.

2. Literature Review

The MRI images analysis is one of the tedious task performed by radiologists or clinical experts where the correct examination of the contents plays a crucial role, [1][2] Has shown that one of the techniques for faster analysis is by following the steps such as the segmentation: which separates the region of interest in the digital picture by using threshold techniques to Mark grey and non grey pixels, detection: which will separate the unwanted regions of the picture, and extraction: Highlight the interested part of infected tumor area from magnetic resonance (MR) images. This tedious process for optimal solution should be done by computerized technology. The medical resonance image segmentation process by [4][5] have investigated the usage of Berkeley wavelet transformation (BWT) based brain tumor segmentation. Furthermore, to improve the accuracy and quality rate the support vector machine (SVM) [8][9] based classifier was proposed, this way the relevant features were extracted from each of the segmented tissue.

The predictions using the deep learning has gained traction over the years. In deep learning, a computer learns to classify images, and other digital data. The computer is trained with large image datasets and then it makes the changes of the pixel value of the picture to an internal interpretation, where the added classifier can detect patterns on the provided image. Deep learning method for image classification is the convolutional neural network (CNN). CNN on MRI images is proving to be efficient method as it learns directly from the image data [6], thus it removes the burden of manual feature extraction. [10] Common problem in image classification using this method is because of over fitting. The maximum trained images with large dataset will be the best model used. The nature of CNN having minimum connection and hyper parameter makes CNN model efficient to train and perform better than other models [12]. Another study by using the local binary pattern they had performed preprocessing and segmentation on the MRI images of Brian [13]. Grouping based on the similarity of data and labeling for the segmentation on the images by using techniques like K-means is well known, technique like erosion and dilation for the edge detection and Morphological operations are alsoused [14].
3. New System Architecture

The most tedious work for a radiologist is segmentation, extraction, and detection of tumor from a MR Image. This section consists of the following items, the source of Livestock MRI dataset, algorithm that has been used to detect the tumor in a specific affected area. Also, the primary concepts that are used for preparing the algorithm are presented. Our proposed methodology is applied on a real image data set that are resized to 64x64-pixel size. The figure.1 details the flow if the CNN and the following section highlights the implementation of the proposed algorithm.

3.1 Pre-processing

Tumor detection can be performed by CNN where the consecutive convuluted layers are used in which the output of a layer becomes the input of next layer this works well with the sprase type of images like MRI , figure.2 highlights the work flow sequence. A Three-Layer and experimental extra layer of Conv2D is used for the proposed tumor detection. This model has the stacked stages of Conv2D where the input of each layer feeds the next layer. Figure 3 details the Algorithm for the overall procedure.

The input MRI is first made to same dimension of 224 x 224 x 3 at Model 2 and 128 x128 for Model 1 of Conv2D [11]. We use the convolution kernel of 2 x 2 which will be convuluted with the input layer .

\[ Y = \sum WiXi + b \]  

\[ \text{Softmax}(Ln) = \frac{e^{Ln}}{\sum e^{Ln}} \]
information of how well the probability distribution function output from the softmax matches the one-hot-encoded log functionality will give how well the prediction is similar to the reality.

\[
\text{Cross entropy} = -\sum_Y Y_i \log(Y_t) \quad \quad (3)
\]

The Brian images such as MRI will have the problem of overfitting where the model is learns the noise and the features of the training data which will impact the overall performance of the model and hence the concept of Max Pooling is chosen to overcome this. Pooling layer is processed after the above convolutional layer to reduce the spatial size (only width and height, not depth). This eventually reduces the number of parameters in consideration, which leads for the computation be reduced. Also, few parameters will reduce the overfitting. The Max pooling is the preferred in general the filter is of size 2*2 with a stride of value 2, Proposed model have used MaxPooling2D for the model 1.

This convolutional layer runs on scaled part of the 128 x 128 x 3 for Model 2 and 224 x 224 on the Model 1.

The next process of Flattening which is one of the main part of the layers after the pooling the flattening will ensure that the pooled data is now made into a single vector which has to be fed to the artificial neural network. This will be the input to the CNN for next processing.

There are overall 128 nodes in the hidden layer. Keeping in mind the computing resources and we need to fit our model we the 128 nodes gives the most reasonable result. ReLU is the activation function used here owing to the fact of sparsity of the input image. Below algorithm shows the overall process.

**Figure 2. Work Flow.**
3.2 Segmentation and Morphological operation

After the Machine learning process once the tumor is detected we need to extract the tumor location. The operation of segmentation in which the separation of pixel values greater than the predefined threshold which are mapped to black and the remaining are mapped to white greyscale. We don’t need that white part, so we need to remove it. We use erosion method of morphology to filter the white part.

Wavelets which are efficiently used for segmentation [10] are used in our approach, in general wavelet is kind of a waveform with a limited time duration and its average value will be zero. A basic wavelet (4) is used for generation of all kinds of wavelets by changing different scaling and the translation parameters, which is defined by

$$\psi_{s,t} = \frac{1}{\sqrt{s}} \psi \left( \frac{t-s}{s} \right)$$  \hspace{1cm} (4)

$s$ and $\sum \tau$ are scaling and translation factors.

The boundary areas of the brain images are extracted by different morphological operations. This is possible only on binary images. The major operation of the morphological involves dilation and erosion. Dilation constitute the process of adding the pixels to the given boundary region and erosion technique involves in removing the pixels from the same boundary regions.

We applied the anisotropic diffusion filter where the noise in the given MRI image is reduced up to 60% and it also helped in the sustenance of grey matter, content in the images, edges in the images. The Gaussian filter we used is of 2D convolution and the width of the image also increased as the parameter number increased. There is no blurring of the images found after we processed and therefore, we got all the required edges in the images. The partial differential functions we used here are incorporated with values like the number of iterations to be as 10 and discrete PDE solution factor to be as 15.

4. Results and Discussions

Different type of data set related to livestock brain MR images are gathered and are processed through our algorithm which include Deep learning CNN Machine Learning Technique, Morphological Operations and finally a function that can send a mail and detected tumor outline image to the livestock farmer’s mail. The following are the results.
The results are as follows and are shown in below in the figure 5, 6 for for this model as shown in the summary figure 9 we have choosen in the model for 30 epochs, we have used the Max Pooling and categorical crossentropy the model parameters as shown in the figure 6 and there was the prediction of 98% achieved and advantage of the Max pooling in which the maximum pixel value from the batch is chosen which generally gives the more prominent sharp features of the image. Along with the categorical cross entropy where the assumption is generally that only one single class will be correct out of all possible ones, while binary_crossentropy where the loss which is calculated for every output vector is not affected by the other component values. The figure 5 and 6 loss and accuracy is also calculated for each of the epoch and considerable prediction of 98% was achieved in the 30 epochs.

Figure 5 Model 1 Loss
Figure 6 Model 1 Accuracy

Figure 7 Model 2 with 20 Epoch
Figure 8 Model 2 with 20 Epoch
The initial part of identifying the Tumor based MRI scan of by the CNN yielded the following results while Model is learning. We observed that by Model 2 figure 12 Where we used the Binary entropy and the Average Pool method l20 Epochs the Machine learning was able to learn the tumor-based images. Compared to the 15 and 10 with the following results of parameters figure [10, 11]

The CNN Model with 20 Epochs yields:

The Accuracy and Loss figure 7 and figure 8 for the prediction showed converge slowly with the parameters and accuracy of 80 percent.

The overall predictions worked well with the above suggestions on the different layers of the Neural network and 20 Epochs set we were able to get the MRI prediction in better manner as the followup of the prediction we need to isolate the tumor for the image is now processed further.
Figure 12. Model 2 Summary

After the predictions are completed, this image consists of artifacts and noise which is to be removed. Figure 15. We used anisotropic diffusion to remove the noise. After the completion of filtering, it is sent to thresholding, and many morphological operations are performed on it which are shown in the figure. Figure 16 and Figure 17. Only the outline of the tumor is shown in this Figure 18. The figure 19 is the marking of the detected tumor.
5. Conclusion

Utilizing the MRI images of the livestock brain, we have made the prediction using the optimal CNN model used based on the Model 1 figure 9 and Model 2 figure 12 which had the difference in the Maxpolling schemes and the loss entropy and we found that model 1 had faster converge for the MRI image and the prediction with 98 percent and Model 2 with the 20 Epochs it was able to learn properly and predictions were success after the predictions we have segmented the parts like grey matter cerebrospinal fluid, and the infected tumor tissues figure 15, figure 16. We also eliminated the unwanted noise present in our image and smoothened the image using different techniques like MMO figure 17.

Next task is to send the image to mail. That is shown in the following image of figure 20 and figure 21.
From the experimental results, we came to conclusion that the proposed method is fast in computation when compared with manual detection by the radiologists and even can yield better results also. One limitation that we found in our work is that it is unable to detect multiple tumors. Even-though the results revealed that the proposed system was accurate to its best. In our future work we would like to combine many types of classifiers to our algorithm so that accuracy of the proposed system can further be increased and predict the probable disease outcomes by few more layers and different Activation parameters of the Machine learning techniques. The application IOT can be extended to direct messaging to WhatsApp in future works.

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