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BRAIN TUMOR DETECTION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract: Brain Tumor segmentation is one of the most crucial and arduous tasks in the field of medical image processing as a human-assisted manual classification can result in inaccurate prediction and diagnosis. Moreover, it becomes a tedious task when there is a large amount of data present to be processed manually. Brain tumors have diversified appearance and there is a similarity between tumor and normal tissues and thus the extraction of tumor regions from images becomes complicated. In this thesis work, we developed a model to extract brain tumor from 2D Magnetic Resonance brain Images (MRI) by Fuzzy C-Means clustering algorithm which was followed by both traditional classifiers and deep learning methods. The experimental study was carried out on a real time dataset with diverse tumor sizes, locations, shapes, and different image intensities. In the traditional classifier part, we applied six traditional classifiers namely- Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multi-layer Perceptron (MLP), Logistic Regression, Naive Bayes and Random Forest. Among these classifiers, SVM provided the best result. Afterwards, we moved on to Convolutional Neural Network (CNN) which shows an improvement in performance over the traditional classifiers. We compared the result of the traditional classifiers with the result of CNN. Furthermore, the performance evaluation was done by changing the split ratio of CNN and traditional classifiers multiple times. We also compared our results with the existing research works in terms of segmentation and detection and achieved better results than many state-of-the-art methods. For the traditional classifier part, we achieved an accuracy of 92.42% which was obtained by Support Vector Machine (SVM) and CNN gave an accuracy of 97.87%

***Index Terms* – Tensor flow, Cnn ResNet-v2, Brain tumor, Filtering, Smoothening filter, Morphology, Segmentation, ,Medical image, SVM**

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I.INTRODUCTION

For medical diagnosis, the interior of a human body is imaged using medical imaging techniques. Yet one of the trickiest and most lucrative areas of image processing is the classification of medical images. The most common issue with medical picture categorization is cancer detection or tumor identification. According to data on the mortality rate of brain tumors, this disease is among the most grave and disturbing.

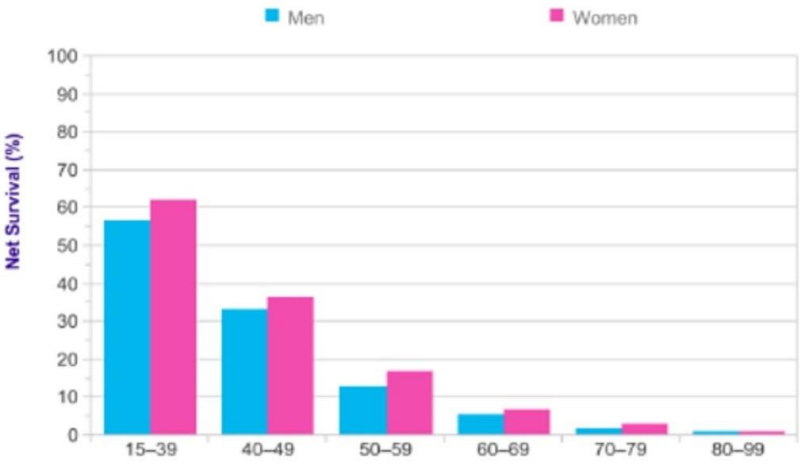
a human body. More than 1,000,000 persons are diagnosed with brain tumors each year worldwide, according to the International Agency for Research on Cancer (IARC), with a steadily rising mortality rate. As compared to cancer, it is the second-most common cause of death in infants and individuals under the age of 34.

At present, doctors use cutting-edge techniques to find tumors that are more unpleasant for their patients. MRI (Medical Reasoning Imaging) and CT (Computerized Tomography) scans are two practical ways to examine anomalies in various sections of the body. Recent times have seen a rise in interest in MRI-based medical image analysis for brain tumor investigations as a result of the rising demand for effective and impartial analysis of significant amounts of medical data.

We chose brain tumor identification and classification, which is a subfield of medical image analysis, after taking into account recent figures on the fatality rate brought on by brain tumors. Medical picture tumor detection takes time since it relies on human judgement. Radiologists and other specialist medical professionals who are experts in this field evaluate CT, MRI, and PET scan images and make recommendations that affect the course of treatment. It takes time to complete this entire process. As it will be carried out by machines, automated medical picture analysis can help to reduce the time, effort, and workload of a human in this situation.

It takes advanced computerized quantification and visualization techniques to analyze this wide range of image formats. So, by eliminating the necessity for manually processing such a large amount of data, automatic brain tumor diagnosis from MRI pictures will be vital in this scenario.

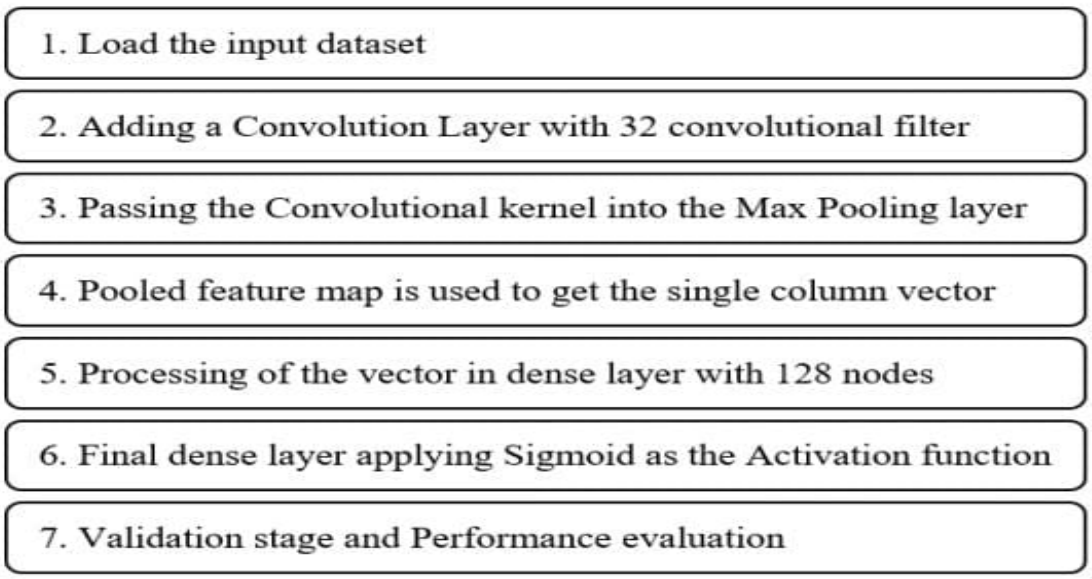
II. NEED OF THE STUDY



Figures indicate that brain cancer has a greater mortality rate than other cancers.
Early brain tumor detection helps lower the mortality rate in this profession. Automated picture analysis will be very helpful in promoting speedier communication, where medical care can be extended utilizing information technology to remote places.

Data and Sources of Data
Even the most effective machine learning algorithms will fall short in the absence of high-quality training data because machine learning models are only as good as the data they are trained on. Early on in the training process, it becomes clear that relevant, full, accurate, and high-quality data are required. Only with sufficient training data can the algorithm quickly identify the features and discover the links required for future prediction. More specifically, the most important factor in machine learning is high-quality training data. The proper data must be used to train machine learning (ML) algorithms, which will then be more accurate and productive.
The terms training dataset, learning set, and training set are also used to refer to training data. Every machine learning model needs it since it enables them to accomplish desired tasks or generate correct predictions. Simply, the machine learning model is built using training data. It demonstrates what the desired result should look like. The model repeatedly studies the dataset to fully comprehend its characteristics and modify itself for enhanced performance. The data set was obtained from a free stock picture source, such as Google, Pinterest, etc., with a variety of image orientations and modulations. In the cloud environment, this dataset is used to train the model.
Data availability: Here the data is freely available and copyright free.

III. RESEARCH METHODOLOGY



Step 1. Perform Exploratory Data Analysis (EDA)
The brain tumor dataset contains 2 folders “no” and “yes” with 98 and 155 images each. Load the folders containing the images to our current working directory. Using the imutils module, we extract the paths for all the images and store them in a list.
Now, we iterate over each of the paths and extract the directory name (no or yes in our case which acts as the label), and resize the image.
Step 2: Build a CNN Model
Convolutional Neural Network or CNN for short is a deep neural network widely used for analyzing visual images. These types of networks work well for tasks like image classification and detection, image segmentation. There are 2 main parts of a CNN:
A convolutional layer that does the job of feature extraction.

A fully connected layer at the end that utilizes the output of the convolutional layers and predicts the class of the image.
Step 3: Train and evaluate the model
The model is trained on epochs (full iterations) with train steps for training set and validation steps for validation set in each epoch. We will evaluate our model using the predict () function.

Algorithm Evaluation process of CNN model

```
loadImage();
dataAugmentation();
splitData();
loadModel();
for each epoch in epochNumber do
    for each batch in batchSize do
        ŷ = model(features);
        loss = crossEntropy(y, ŷ);
        optimization(loss);
        accuracy();
        bestAccuracy = max(bestAccuracy, accuracy);
return
```

IV. SYSTEM ANALYSIS

HARDWARE REQUIREMENTS:
1. SYSTEM: Intel/AMD processor with a minimum clock speed of 1.3 GHz
2. HARD DISK: 20 GB or more
3. MONITOR: 15 VGA COLOR
4. RAM: 32 GB or more

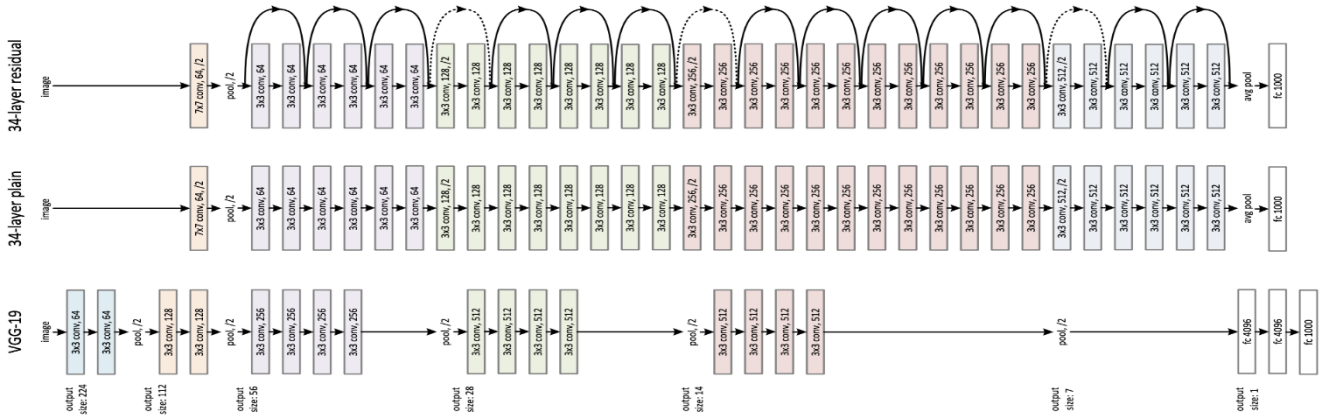
FUNCTIONAL REQUIREMENTS:
Input: The brain MRI image is given as input
1.Skull part in the MRI image will be removed
2.Then the MRI image is filtered and enhanced and later we segment the abnormal tissues
3. Finally the tumor is contoured.
Output: Tumor is being detected from the input image given

NON-FUNCTIONAL REQUIREMENTS:
1. Execution qualities: Efficiency
2. Evolution qualities Testability
3. Extensibility
4. Scalability
5. Usability
6. Reliability
7. Performance
8. Supportability
9. Implementation

WORKING MODEL:
ResNet-50 v2 Architecture
The original ResNet architecture was ResNet-34, which comprised 34 weighted layers. It provided a novel way to add more convolutional layers to a CNN, without running into the vanishing gradient problem, using the concept of shortcut connections. A shortcut connection "skips over" some layers, converting a regular network to a residual network.
The regular network was based on the VGG neural networks (VGG-16 and VGG-19)—each convolutional network had a 3×3 filter. However, a ResNet has fewer filters and is less complex than a VGGNet. A 34-layer ResNet can achieve a performance of 3.6 billion FLOPs, and a smaller 18-layer ResNet can achieve 1.8 billion FLOPs, which is significantly faster than a VGG-19 Network with 19.6 billion FLOPs (read more in the ResNet paper, He et, al, 2015).

The ResNet architecture follows two basic design rules. First, the number of filters in each layer is the same depending on the size of the output feature map. Second, if the feature map's size is halved, it has double the number of filters to maintain the time complexity of each layer.

Architecture



Special characteristics of ResNet-50

ResNet-50 has an architecture based on the model depicted above, but with one important difference. The 50-layer ResNet uses a bottleneck design for the building block. A bottleneck residual block uses 1×1 convolutions, known as a "bottleneck", which reduces the number of parameters and matrix multiplications. This enables much faster training of each layer. It uses a stack of three layers rather than two layers.

The 50-layer ResNet architecture includes the following elements, as shown in the table below:

- **A 7×7 kernel convolution** alongside 64 other kernels with a 2-sized stride.
- **A max pooling layer** with a 2-sized stride.
- **9 more layers 3**×3,64 kernel convolution, another with 1×1,64 kernels, and a third with 1×1,256 kernels. These 3 layers are repeated 3 times.
- **12 more layers** with 1×1,128 kernels, 3×3,128 kernels, and 1×1,512 kernels, iterated 4 times.
- **18 more layers** with 1×1,256 cores, and 2 cores 3×3,256 and 1×1,1024, iterated 6 times.
- **9 more layers** with 1×1,512 cores, 3×3,512 cores, and 1×1,2048 cores iterated 3 times.

(Up to this point the network has 50 layers

FUNCTION:

1. Sigmoid (Logistic)

The Sigmoid function (also known as the Logistic function) is one of the most widely used activation functions. The function is defined as:

Sigmoid activation function (Image by author) The plot of the function and its derivative. the plot of Sigmoid function and its derivative (Image by author) As we can see in the plot above,

The function is a common S-shaped curve. The output of the function is centered at 0.5 with a range from 0 to 1. The function is differentiable. That means we can find the slope of the sigmoid curve at any two points. The function is, monotonic but the function's derivative is not

TRANSFER-LEARNING WORKFLOW:

The typical transfer-learning workflow This leads us to how a typical transfer learning workflow can be implemented in Kera's:

Instantiate a base model and load pre-trained weights into it. Freeze all layers in the base model by setting trainable = False.

Create a new model on top of the output of one (or several) layers from the base model. Train your new model on your new dataset.

V. ALGORITHMS AND LIBRARIES:

CNN CLUSTERING:

Convolutional Neural Network is broadly used in the field of medical image processing. Over the years lots of researchers tried to build a model which can detect the tumor more efficiently. It is a class of deep neural networks which is applied to interpreting visual imagery. A fully connected neural network can detect the tumor, but because of parameter sharing and sparsity of connection, we adopted the Convolutional Neural Network (CNN) for our model.

Python:

It has a large and broad library and provides a rich set of modules and functions for rapid application development. GUI Programming Support: Graphical user interfaces can be developed using Python.

TensorFlow:

It is a Python-friendly open-source library for numerical computation that makes machine learning and developing neural networks faster and easier TensorFlow allows developers to create dataflow graphs—structures that describe how data moves through a graph, or a series of processing nodes.

VI. SYSTEM TESTING:

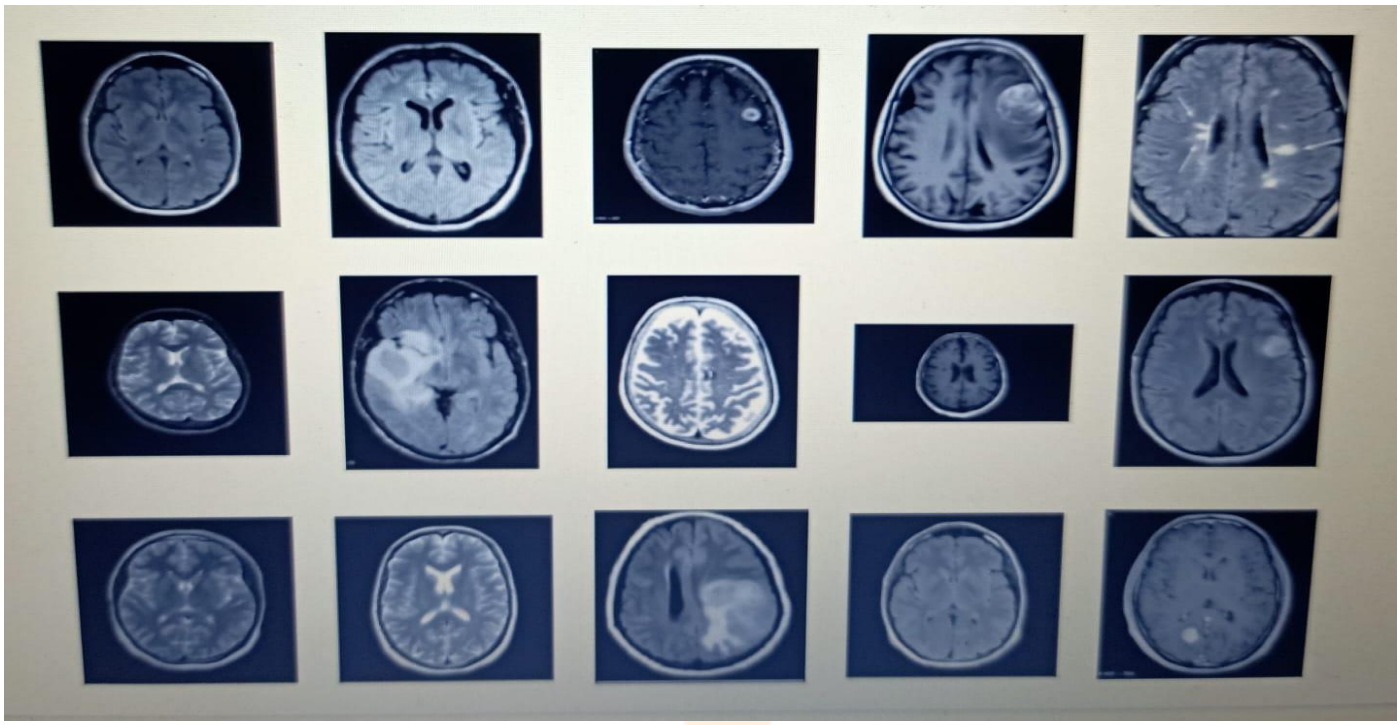
Testing is centered on the following items:

Valid Input: identified classes of valid input must be accepted.

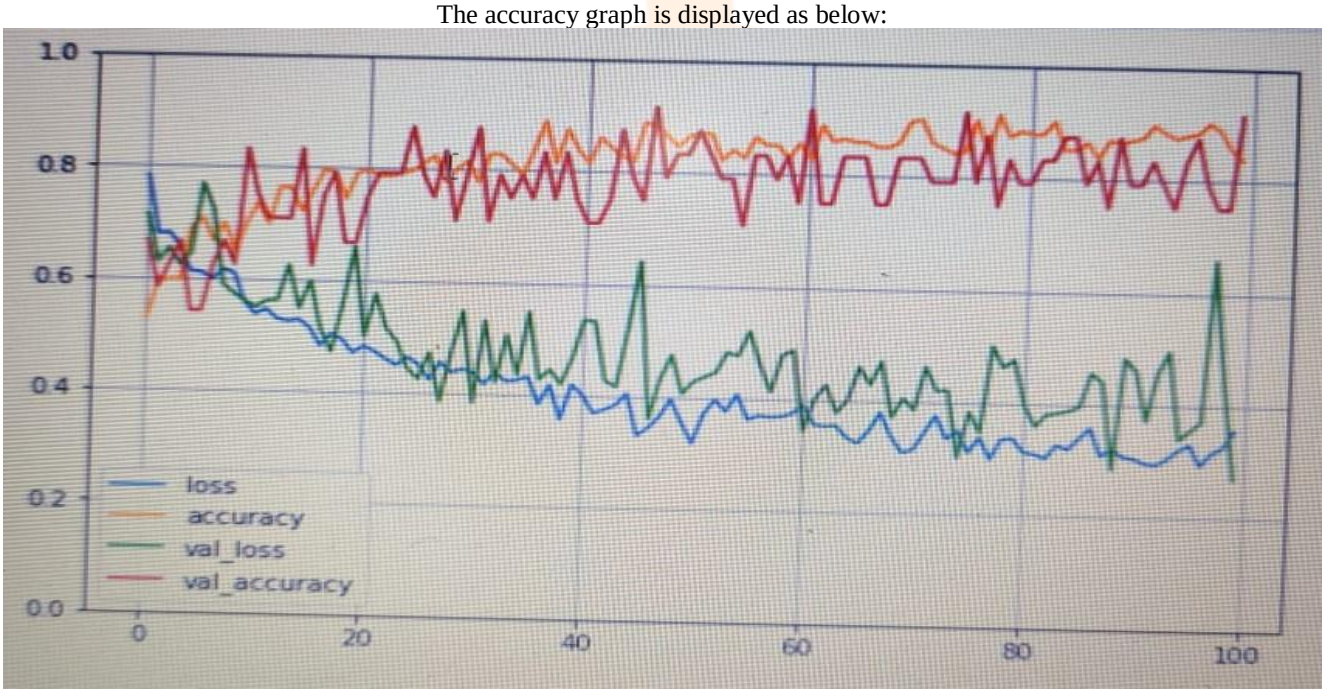
Invalid Input: identified classes of invalid input must be rejected.
Functions: identified functions must be exercised.
Output: identified classes of application outputs must be exercised.
Systems/Procedures: interfacing systems or procedures must be invoked. Organization and preparation of different tests are focused on requirements, key functions, or special test cases.
In addition, systematic coverage pertaining to identifying Business process flows; data fields, predefined processes, and successive processes must be considered for testing. Before all types of testing are complete, additional tests are identified and the effective value of current tests is determined.

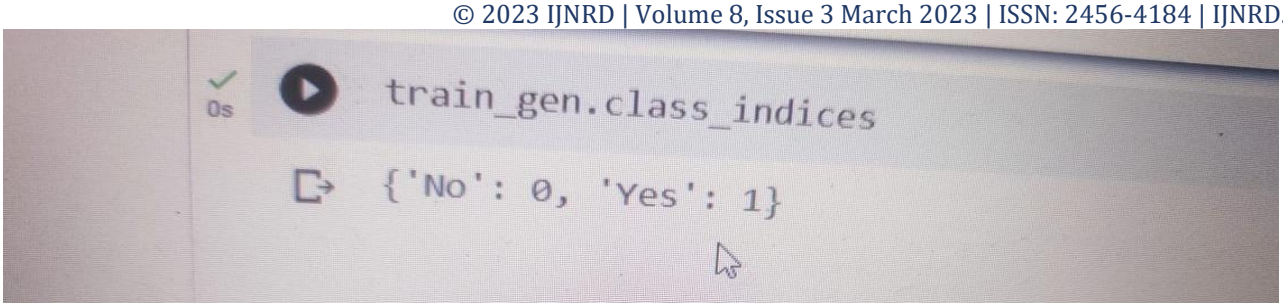
VII. RESULTS AND DISCUSSION

The following diagram represents whether tumor is present or not
The circle in the image indicates the presence of tumor.



The accuracy graph is displayed as below:





It's the most popular performance matrix which measures how often the classifier produce the correct prediction. Mathematically Accuracy defined as the ratio of the number of correct predicted images and the total number of images and symbolically represented as

Accuracy = (Correct Predictions) / (Total number of images)

Where https://onedrive.live.com/edit.aspx?resid=274AB16743D55337!187&ithint=file%2cdocx&authkey=!AB4s6P4_k2yvCZQ TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives

Accuracy is defined as **(TP+TN)/(TP+TN+FP+FN).**

VIII. CONCLUSION

In our work, we have undertaken performance analysis of automated brain tumor detection from MR imaging employing fundamental image processing approaches based on several hard and soft computing. Subsequently, in order to incorporate deep learning methodology into our study, we applied CNN for brain tumor identification. We contrasted CNN's output with the output of the traditional model with the best accuracy (SVM). Also, our research offers a general approach to tumor detection and feature extraction.

For greatest effectiveness when applied to the entire dataset, parallelization and the use of a high-performance computing platform are required. Although we made every effort to precisely detect tumors, there were a few instances during the course of our study where this was not possible or where the tumor was misidentified. We will therefore attempt to operate on both those photographs and the entire dataset. So that we may obtain a more accurate and superior outcome, we will attempt to apply additional deep learning techniques in the future.

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