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Brain Tumor Detection Using Convolutional Neural Network

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Abstract* — Tumor is the abnormal development of cells in the body. The fairly significant overgrowth of brain cells is known as a brain tumor and classification manually takes time and is only possible at a few diagnostic facilities. Therefore, it is necessary to create a system that can identify the type of brain tumor based solely on the input MR images. To evaluate these malignancies, a common imaging approach is magnetic resonance imaging (MRI), however, manual segmentation cannot be done in a timely manner due to the volume of data generated by MRI, restricting the application of exact quantitative measurements in clinical practice. This study presents a novel hybrid methodology for the classification of brain cancers based on the analysis of magnetic resonance imaging (MRI) data. The methodology compares the performance of different classifiers, namely Convolutional Neural Networks (CNNs), K-nearest neighbor, Support Vector Machine and Logistic Regression in predicting the presence of brain tumors. The CNN model is specifically employed to get features from the MRI data and apply them to the classifiers. The results of the study show that the different CNN models, along with KNN, SVM, LR, and Long Short-Term Memory Networks were taken for tumor classification. The achieved accuracies were 82.35%, 78.43%, 61.26% and 74.28% respectively. Among these algorithms, KNN demonstrated the highest accuracy, indicating its effectiveness in accurately classifying brain tumors based on the MRI data. By integrating these classifiers and utilizing the CNN model for feature extraction, this hybrid methodology presents a promising method for classifying brain tumors from MRI data. The findings highlight the potential of combining deep learning techniques like CNNs with traditional machine learning algorithms to increase the reliability of diagnosing brain tumors and contribute to the field of medical image analysis.

***Keywords* — Brain tumor, cancer, SVM Classifier, KNN Classifier, Convolution Neural Network.**

I. INTRODUCTION

A brain tumor is a clump of abnormal cells that has grown in the brain. A hard skull protects the human brain inside. Any expansion in such a restricted space will result in serious problems. There are both malignant and non-cancerous brain tumors. As benign or malignant tumors grow, the pressure inside the skull will increase. A lasting brain injury or possibly death will follow from this. There are over 700,000 brain tumor sufferers globally, and 87,000 new cases were diagnosed in 2019 alone. Since 2019, the cumulative mortality count due to intracranial neoplasms amounts to 16,900 individuals, with a meager overall survival rate of approximately 36%.

The two imaging modalities, MRI and CT , are regularly used to identify anomalies in the size, shape, or location of brain tissues, which in turn aid in the detection of cancers. MRI is recommended more by physicians. Consequently, magnetic resonance imaging (MRI) has garnered heightened scrutiny and interest among the scientific and research communities. Doctors typically employ traditional scrutiny when finding brain malignancies from MRI scans. However, automated methods and computer-assisted medical image processing techniques are increasingly used by doctors to detect brain tumors. Machine learning algorithms can forecast the class labels of ambiguous data objects by using training data samples as a source of knowledge. Healthcare organizations can frequently utilize ML(Machine Learning) algorithms.

The major goal of this study is to investigate the methods used to identify brain tumors using various image processing techniques. In order to detect brain cancers, it is also important to examine how well various image processing methods work with MRI scans. This research article presents a novel approach for the precise identification and localization of brain tumors by utilizing a combination of conventional classifiers and convolutional neural networks (CNNs). The proposed method aims to enhance the efficiency of tumor segmentation and detection processes.

II. LITERATURE REVIEW

[1] The work in this research is focused on using LBF SVM to identify and detect brain tumors. After testing, it was found that implementing a brain tumor identification strategy with LBF SVM improved the effectiveness of finding the brain disease with merit. After thorough testing, the proposed system's experimental results are examined, and the findings are rated using evaluation metrics. According to experimental findings, employing a linear function support vector machine, 64 % of tumors can be identified accurately, giving the classifier a high overall accuracy rate.

[2] This academic paper discusses segmentation using Unet architecture with ResNet50 as the foundation, which produced an intersection over union level of 0.9504 on the data set (IoU). To improve the classification rate, the concepts of pre-processing and data augmentation were introduced. DenseNet201, MobileNet V2, ResNet50, and InceptionV3are a few additional deep learning methods that are deployed. Several CNN models are used to classify tumors with accuracy such as MobileNet V2 (91.8%), Inception V3 (92.8%), ResNet 50 (92.9%), and DenseNet 201 (93.1%) and NASNet-99.6%, respectively. To hold out important features from MRI slices, two transfer learning techniques: freeze, fine-tune are used.

[3] The suggested hybrid model integrated threshold-based segmentation with threshold-based classifiers (CNN and SVM) for classification and Support Vector Machines for detection. The accuracy of the various models used in the past experiments ranged from Rough Extreme Learning Machine (RELM) to 94.2 % to Deep and Convolutional Neural network to 95 % to Discrete Wavelet Autoencoder with Deep Neural Network to 96.1 % to CNN to 97.5 %. The hybrid CNN-SVM model has featured 98.5 % compared to other models, accuracy.

[4] The suggested system's goal is to divide brain tumor images into three subtypes utilizing (SVM) and (CNN) technology: meningioma, glioma, and pituitary (SVM). The dataset images are compressed to save on processing, and salt noise is added to strengthen the model and expand the dataset. CNN classifier and an SVM classifier are used in creating the detection model. The Classifier is trained using 80% of the data collected and tested using the remaining 20% of the data set.

[5] The author Priyanka Aiwale describes a methodology for tumor detection in the brain with the help of KNN algorithm, LLOYD clustering and software as a MATLAB. It calculates the area occupied by brain tumors by using the proposed algorithm. As per the area it decides the complexity and treatment of that brain tumor patient. This model has accurately identified 80% of the brain tumor patients.

[6] The author of the paper is Prof. G. Sasibhushana Rao describes a hybrid model of CNN-KNN.They Have used CNN to extract the features and KNN is used to classify the given input data into the output classes. It classifies the input data with 96.25% accuracy.

[7] In this study, the first author employs six classic classifiers: Support Vector Machine, K-Nearest Neighbour, Multilayer Perceptron, Logistic Regression, Naive Bayes, and Random Forest.They were all made with Scikit-Learn. He subsequently progressed on to CNN, which is built with Keras and Tensorflow libraries and outperforms traditional ones. CNN achieved an impressive 97.87 percent accuracy rating in this study. The prime goal of this research is to discriminate between normal and abnormal pixels using statistical and texture-based methods.

[8]The author of this research proposes a method using Convolutional Neural Networks classification to axiomatically detect brain tumors. The deep architecture is designed using minute kernels. The neurons are said to light in weight. CNN archives have an accuracy rate of 97.5%, which is low in complexity and superior to all other state-of-the-art procedures, according to trial findings.

[9] In this study, the author investigates small 3X3 kernels as part of convolutional neural network (CNN) based automatic segmentation approach. Using tiny kernels is advantageous because the network has fewer weights. allows for the design of more intricate architectures while also preventing overfitting. Additionally, they looked into the use of intensity normalization as a preliminary processing step., which, while uncommon in CNN-based segmentation approaches, proved to be quite successful when combined with data augmentation for segmenting brain tumors in MRI images.

[10] In this paper, the author develops a hybrid technique based on neurophilosophy and convolutional neural networks in this research. It attempts to discriminate between benign and malignant tumor locations in brain image segments. The results demonstrated that CNN features outperform a variety of classifiers in classification.

Experiment results reveal that CNN features outperformed SVM in classification performance, The simulation results were used to check the output data, with an average success rate of 95.62 percent.

[11] The author of the paper is P Gokila Brindha, who proposed a model that uses ANN and CNN. In this model ANN is used for training, which has 7 layers.After training of the model it uses the CNN for testing purpose. After applying the ANN model on training data it gives 97.13% accuracy.

[12] The paper likely focuses on addressing the challenge of accurately classifying brain tumors using medical imaging data. It acknowledges the success of CNNs in image classification tasks but emphasizes the difficulty of applying them directly to 3D medical image classification. To overcome this limitation, the authors introduce a cascaded framework that incorporates LSTM networks.The proposed framework likely involves using CNNs to extract features from medical images, followed by feeding these features into LSTM networks for further processing and classification. The LSTM networks would be employed to capture temporal dependencies and long-term contextual information in the sequential data. The paper presents experimental results and evaluation metrics to demonstrate the effectiveness of the proposed CNN-LSTM framework for brain tumor classification. It compares its approach to other methods, potentially showcasing advantages such as improved accuracy or robustness.

[13] In this paper A novel strategy based on long short-term data is offered to tackle the limitations of automated brain tumor classification Using LSTM model with magnetic resonance images (MRI). First, 5 x 5 Gaussian filters are used to improve the quality of multi-sequence MRI. In this research four-layer deep LSTM model is used for brain tumor classification. The proposed approach is divided into two stages. Preprocessing is used to normalize the intensity of MRI data. The LSTM model is then used for feature learning. Then, for binary classification, fully linked and softmax layers are utilized.

[14] The paper presents LSTM Multi-modal UNet as an effective architecture for brain tumor segmentation in multi-modal MRI. By combining multi-modal UNet with LSTM, the proposed model captures intermodal correlations and temporal dependencies, leading to superior segmentation performance compared to traditional UNet approaches. The paper's future directions, including leveraging UNet++ and exploring weakly supervised learning, provide potential pathways for enhancing the model's efficiency and accuracy in future research. The paper outlines several avenues for future research. Firstly, the authors propose learning from UNet++ to reduce model complexity and improve the segmentation speed of individual images. This optimization could make the proposed architecture more practical for real-time applications. Additionally, the exploration of weakly supervised learning methods holds promise for further improving the algorithm's performance.

[15] The review reveals that automated brain tumor segmentation for use in brain research is a critical task. Traditional techniques for glioma segmentation often face challenges in translating prior knowledge into probabilistic maps or selecting representative features for classifiers. However, Convolutional Neural Networks (CNNs) offer advantages in automatically learning complex features from both normal brain tissues and tumor tissues directly from multiple MRI scans. Convolutional Neural Networks (CNNs) have demonstrated significant potential in enhancing the precision of brain tumor segmentation. Through a comparative analysis of the reviewed literature, this paper highlights the advancements made in brain disease detection using deep learning techniques. By presenting a comprehensive overview of the present state of research, this literature review contributes to the existing knowledge and provides insights for future studies. This literature review emphasizes the importance of early detection of brain tumors and the role of deep learning techniques in improving accuracy and reducing errors in diagnosis.

[16] The review explores the anatomical features of these tumors and their implications for detection and analysis. This review surveys different enhancement methods, such as filtering, histogram equalization, and contrast adjustment, and evaluates their effectiveness in enhancing tumor visibility. Overview of existing segmentation methods, including traditional image processing techniques and advanced algorithms based on deep learning. The review covers different classification techniques, including traditional machine learning algorithms and deep learning approaches.the application of deep learning methods, transfer learning approaches, and the potential role of lightweight techniques like quantum machine learning in improving accuracy and efficiency.

[17] With CNN designs such as ResNet, transfer learning is often used to address the lack of data problem when using a pre-trained DL model generated for one task as a starting point to attack another task. will be used. This study uses transfer learning to build a DL model for classifying MRI images containing

brain malignancies. The proposed approach is used to classify MRI images into 'tumor' or 'non-tumor' using three pre-trained deep CNN models: ResNet, Xception and MobilNet-V2. The experimental results of this study show that pre-trained deep learning models can be used to develop classifiers that can identify malignant tumors in brain MRI, despite the limited size of the datasets used. Specifically, we demonstrated that the MobilNet v2 deep learning model outperformed his two other models by achieving very good performance in terms of accuracy.

[18] In this study, we automatically classified brain cancers based on MRI scans by extracting features using deep learning-based convolutional neural networks . Three types of CNNs (Inception-V3, VGG-16, and VGG-19) were used in addition to traditional CNNs to study the use of transfer learning. The last layers of the models were fine-tuned to increase accuracy. When transfer learning is used to a CNN, high accuracy is achieved faster and with a smaller dataset. Inception-accuracy V3's is surpassed by VGG19's accuracy of 97 percent and VGG-16's accuracy of 96 percent (89 percent). The suggested segmentation approach, which combines transfer learning with CNNs, offers more reliable and robust segmentation technique

[19] This study aims to assess how well nine pre-trained transfer learning classifiers perform including Inception Resnet V2, Inception V3, Xception, Resnet18, Resnet50, Resnet 101, Shufflenet, Densenet 201 and Mobilenetv2. Deep transfer learning techniques are most commonly used to detect and classify the three most common types of brain tumors: meningioma, glioma, and pituitary. To this end, we use state-of-the-art, pre-trained TL approaches to determine or detect gliomas, meningiomas, and pituitary type of brain tumors. The Inception Resnet v2 TL algorithm can be considered the best classification algorithm, as fine-grain classification experiments have shown that it can more accurately and efficiently identify and classify gliomas, meningiomas, and pituitary brain tumors. can. Using the Inception Resnet v2 TL algorithm, it outperforms other DL techniques, achieving 98.99 percent accuracy, 98.30 percent accuracy, 99.80 percent recall, and 99 F-score of 10 percent.

[20] A mechanism for classifying brain tumors according to grade was suggested by the author Maedeh Sadat Fasihi. The LSTM classifier then receives this set as input. Both the feature selection process and classifier design were examined using several alternatives. The study's findings show that, in comparison to utilizing each transform alone, the suggested approach, which combines DWT and DCT, improves accuracy without incurring a substantial time penalty. In terms of accuracy, the suggested system performs better than the baseline network. Overall, the suggested technique may be used to many already available medical imaging scans, where not every picture is labeled.

[21] In this article, authors developed a CNN with LSTM cascade model for the brain to explore volumetric classification of tumors into high-grade and low-grade gliomas. Thanks to the superior performance in extracting high-quality feature representations of the VGG-16 model compared to other state of the art CNN architectures, LSTM effectively distinguishes between his HG and LG gliomas can. This method also has the advantage of being suitable for multidimensional 3D data. We extend this method to segmentation tasks in the future by building a model that can perfectly predict brain tumor pixel markers using a small amount of training data.

[22] The goal of this study is to develop a deep layer with highest accuracy and lowest computational complexity that can mimic the diagnostic process that medical professionals use to review all MRI sequences of a single patient to find cancer. The approach of collectively evaluating all MRI sequences and using ablation studies to build CNN models to achieve the highest accuracy with minimal time complexity will be useful in further studies and in real cancers.

III. PROPOSED METHODOLOGY

In Brain tumor detection Deep Learning Algorithms and machine learning were used to develop a machine learning model to predict whether the provided input of an MRI scan demonstrates a normal brain (non-tumor brain) or an abnormal brain (brain with tumor). The dataset used for the classification of the brain tumor is an image dataset containing the images of Brain MRI scans of healthy and diseased people. The dataset includes 253 MRI scan reports with 155 yes and 98 no. The tools used for the preparation of the model were Google Colab and Python libraries. The Algorithms used for classification are Convolution Neural Network (CNN), SVM, KNN, and LR. This project's prime objective is to use CNN to take characteristics out of the dataset and use them in the classifiers to check which of them provides maximum accuracy on the used dataset.

The process to accomplish the aforementioned task involves the following steps:

1. Importing the necessary libraries: Python libraries Keras, TensorFlow, OS, and sk-learn were used to import various functionalities required for the creation of the model.

2. Loading the dataset: The image dataset was loaded from Google Drive to the Google Colab environment and the library os was used to implement it into the model.

3.A model consisting of 8-layer architecture was created for classification. A 2D convolutional layer with 64 filters, each measuring 3x3, makes up the model's first layer, and uses the 'relu' activation function. The input shape of each image is 128x128 with a single-color channel. The second layer is another 2D convolutional layer with 32 filters, also of size 3x3, and using the 'relu' activation function. The third layer is a max pooling layer with a pool size of 2x2 and 'valid' padding. The fourth and fifth layers of the Convolutional Neural Network (CNN) architecture in this study consist of 2D convolutional layers. These layers are responsible for extracting relevant features from the input data.In the fourth layer, there are 32 filters applied to the feature maps generated from the previous layer. These filters are small matrices that perform convolutions on the input data, sliding across the input and computing dot products with local regions. The resulting feature maps highlight specific patterns or features present in the input. The activation function used in both the fourth and fifth layers is the Rectified Linear Unit (ReLU). The ReLU activation function introduces non-linearity into the network by setting negative values to zero and keeping positive values unchanged. This nonlinearity allows the network to learn more complex representations and helps prevent the vanishing gradient problem.The use of 32 filters in the fourth layer and 16 filters in the fifth layer allows for the extraction of multiple different features at different levels of abstraction. These layers build upon the previous layers' learned representations and further refine the feature maps to capture more detailed information about the input data. By incorporating these 2D convolutional layers with specific filter sizes and ReLU activation, the network becomes capable of detecting and representing intricate patterns and features relevant to brain tumor detection. Max pooling layer is the sixth layer with a pool size of 2x2. During the max pooling process, the feature map is divided into non-overlapping regions of the specified pool size (2x2 in this case). Within each region, the maximum value is extracted. This maximum value represents the most prominent feature within that region. The results of the maximum pooling operation is a down-sampled feature map that retains the most salient features while reducing the spatial dimensions. Moving on to the seventh layer, it is a flattening layer. This layer converts the 2D feature maps generated by the previous layers into a 1D feature vector. The purpose of this flattening operation is to transform the spatially organized features into a format suitable for input into a layer that is entirely connected. By flattening the feature maps, the information from different spatial locations is combined into a single vector, which can then be fed into subsequent dense layers for classification or further analysis. A single neuron in the dense, completely linked final layer has a "sigmoid" activation function

As per the CNN model, training was conducted for a total of 55 epochs. The number of epochs was determined based on experimentation and monitoring the model's performance on a validation set. The model's training progress was observed, and it was found that the validation loss and accuracy improved steadily for the first few epochs and then started to plateau. Therefore, after 55 epochs, it was determined that the model had reached a point of diminishing returns, where further training was unlikely to significantly improve its performance in fig.1. This choice of 55 epochs aimed to strike a balance between capturing the patterns in the data and avoiding overfitting, resulting in a model that achieved satisfactory performance on unseen data.

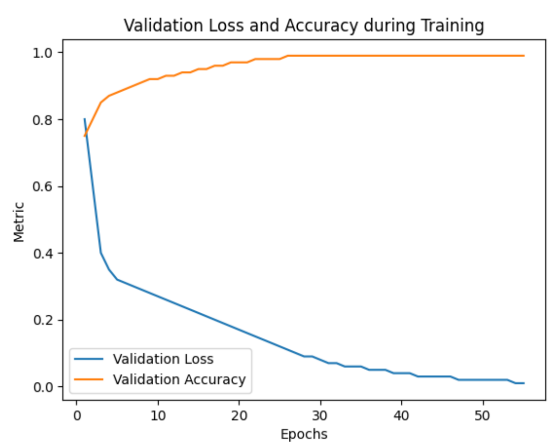

Fig 1:Training Progression of a CNN Model with 55 Epochs - Validation Loss and Accuracy

4.Compilation of the created model. The results of the CNN algorithm are compiled by choosing the appropriate loss function, optimizer, and metrics. Our model employs binary cross-entropy as the loss function, specifically designed for binary classification tasks. We utilize Adam optimization algorithm, which is known for its efficiency in updating the model's parameters during the training process, and accuracy as the metrics.

After the compilation of the above steps, our model is ready for evaluation and classification. We use CNN, CNN + Logistic Regression, CNN + SVM, and CNN + KNN for evaluating the model performance. The classifier algorithm which provides the highest accuracy is considered to be the most optimal algorithm when working with CNN. An epoch value of 50 was used in all of the algorithms while training the model.

CNN: In this algorithm, we use the evaluate() function to predict the accuracy of our CNN model. The results obtained from this evaluation will then be used for comparing it with other algorithms to understand about the algorithm which provides the best results on our dataset.

Normalization: Normalization of the dataset was done by dividing each pixel value of the image by 255 which scales the pixel value in the range between 0 and 1. The values will be further used as features in other classifiers.

Splitting the dataset: The dataset was split into training and testing sets. The training set is used to help the model learn about various aspects of the image that can later help to classify any image provided by the testing set into two categories.

Creation of the CNN model: Indicating whether the input image contains a brain tumor or not. The compile() method is used to configure the new model for training. It specifies the loss function to use, which is binary cross-entropy in this case, the optimizer to use, which is the Adam optimizer, and the evaluation metric to use during training, which is accuracy.

Logistic Regression: Combining a trained CNN model with a logistic regression (LR) model involves several steps. First, the CNN model is trained on labeled data, extracting meaningful features. Then, intermediate layer outputs, known as feature maps, are extracted. These features are flattened or pooled to prepare them for the LR model. The LR model is trained separately on the extracted features using supervised learning. Once both models are trained, the output of the CNN model is used as input to the LR model. The LR model applies its learned parameters to produce a binary output. Optionally, the combined model can undergo further fine-tuning on a smaller labeled dataset. This combination leverages the CNN's feature extraction capabilities and the LR model's discriminative power, enabling the capture of complex patterns and relationships in the data. By combining these models, a binary output can be obtained based on the learned features. This approach provides a flexible and powerful framework for various tasks, such as image classification or sentiment analysis.

Support Vector Machine: In this algorithm, we extract features from the training data using the pre-trained CNN model, reshape them, and train a support vector machine (SVM) model on these features First, the extracted features from the CNN model are obtained by passing the training data X_train through the model using the predict method. The resulting features are flattened into a 2D matrix using the reshape method. This reshaped feature matrix is then used to train the SVM model using the SVC class with a linear kernel. Next, the SVM model is used to predict the labels of the test features using the predict method on the SVM model object. These predicted labels are stored in the svm_preds variable. To determine the accuracy of the Support Vector Machine (SVM) model on the test data, the predicted labels are compared with the true labels in the y_test dataset. This process involves calculating the number of correct predictions made by the SVM model. The correct predictions are then divided by the total number of test samples. The resulting value is multiplied by 100 to obtain the accuracy as a percentage. This accuracy metric provides an evaluation of how well the SVM model performs in classifying the test data based on the predicted labels. It quantifies the proportion of correctly classified samples out of the total number of samples in the test dataset. By using this approach, the accuracy measurement provides a quantitative assessment of the SVM model's performance in terms of its ability to correctly classify the test data.

KNN: In this code block, the data is flattened for KNN and then the KNN model is trained and evaluated. The K-Neighbors Classifier() function is used to create a KNN model with a k value of 5. The training data is employed to train the model by applying the fit() function, enabling the model to learn from the provided information. Subsequently, the predict() function is utilized to obtain predicted labels for the test data, and the accuracy is determined by comparing these predicted labels to the actual labels through the mean() function. Finally, the predictions made by the CNN model on the test data are compared with the actual labels. The predicted labels are obtained using the predict() function on the test data from the CNN model. Since the output of the last layer of the model is a probability value between 0 and 1, the predicted labels need to be converted to binary values (0 or 1). This is done using the astype() function which converts the predicted probabilities to binary labels by considering a threshold of 0.5.

Long Short-Term Memory Networks(LSTM): Recurrent neural network (RNN) architectures called Long Short-Term Memory (LSTM) networks are made to handle sequential data and get over the vanishing gradient issue. A recurrent neural network (RNN) is a type of neural network that possesses the ability to model and simulate temporal dependencies. Recurrent Neural Networks (RNNs) possess a feedback connection within their units, enabling them to retain and utilize their internal hidden state, thereby capturing and representing dynamic temporal patterns. It includes three gates: an input gate, a forget gate, and an output gate. The input gate controls relevant information flow into the memory cell, the forget gate allows the model to discard unnecessary information, and the output gate determines what information should be conveyed to the next step or final output. These gates help the LSTM capture important information over long sequences, address the vanishing gradient problem, and effectively process sequential data with long-term dependencies as shown in Fig 2. It is a two-layer neural network with 100 nodes each, concealed between the layers. Because of these gates, LSTM is simpler to optimize because the input characteristics can pass through the hidden layer without affecting the output. The features from the volumetric MRI data of yes and no are used in this work as input to the LSTM with the pretrained data using CNN. The sequential slices extracted from the volumetric data of each subject are utilized to populate the temporal dimension of the Long Short-Term Memory (LSTM) model.

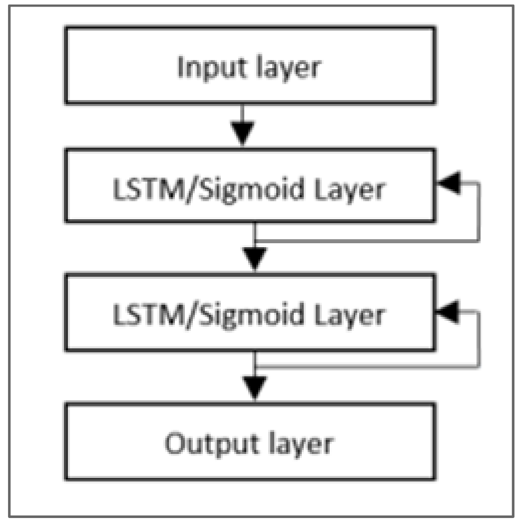

Fig 2: Architecture of LSTM in stacked two layers

IV. RESULT AND CONCLUSION

This research paper compared different machine learning models for brain tumor detection, including CNN, SVM, LR, LSTM, and KNN. The study aimed to identify the model with the highest accuracy. After conducting experiments and evaluations, the experimental results revealed that Convolutional Neural Networks (CNN) exhibited superior performance compared to alternative models in terms of accuracy. CNNs excel in extracting complex features from medical images and have strong pattern recognition capabilities. The recommendation is to use CNNs for brain tumor detection, although further research is needed to optimize these models and evaluate their performance on larger datasets. The ultimate goal is to improve early detection and patient outcomes in brain tumor cases.

The Brain tumor is one of the significant problems that needs to be addressed in the early stages in order to provide the necessary treatment as delaying the process further can result in fatal conditions. The brain tumor detection is thus a useful step in identifying the Brain tumor using MRI scan reports as it predicts the tumor almost instantly and this can be helpful when people cannot have immediate access to doctors to read the report.

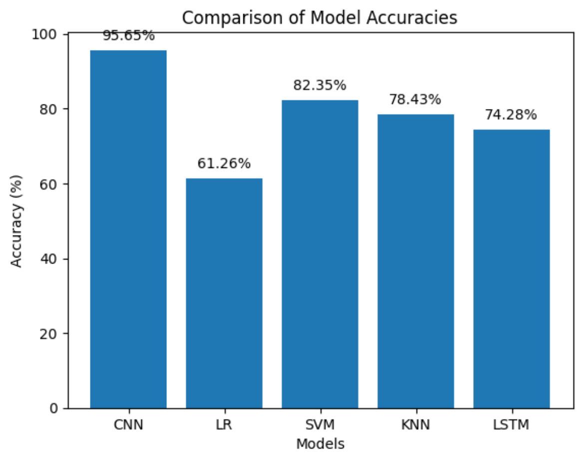

Fig 3: . Graphical representation of percentage of accuracies of different implemented algorithms

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