Diagnosis of Brain Tumor Using Deep Learning Stacked Classifier -Ml Algorithms

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Abstract:-Brain tumours are very lethal, and radiologists have a difficult time classifying them due to the varied characteristics of tumour cells. Recently, computer-aided diagnostic (CAD) systems have shown promise as an enabling tool for detecting brain tumours using MRI. The bottom layers of natural photos and medical images are distinct, although both are used in modern applications of pre-trained models. This research presents a strategy for early identification of brain tumours that involves the extraction and concatenation of many characteristics at different levels. These results are credible since VGG-16 is a pretrained deep learning model. These two models were used to compare two scenarios for identifying and categorising brain tumours. To begin classifying brain tumours, characteristics were first retrieved from various VGG modules using the pretrained VGG_16 model. Second, we used PCA, LDA, and ICA to derive features. These merged characteristics were then fed into a hybrid classifier to determine the kind of brain tumour. Finally, the presence of brain tumour is be identified.The results obtained using matlab tool are compared in terms of various parameters evaluated.

Keywords*: Machine learning Algorithms ,PCA Algorithm, ICA Algorithm ,LDA Algorithm,VGG-16*.

1.Introduction

A mind growth is an uncontrolled multiplication of synapses. The cerebrum cancer could possibly be harmful. Cancers of the cerebrum have their starting points there. Essential mind growths are the most widely recognized sort of harmful cerebrum cancer. Cerebrum malignant growth is a consequence of metastasis, the spread of disease from one more segment of the body.These tumours are known as metastatic brain tumours or secondary brain tumours. Recently, computer-aided diagnostic (CAD) systems have shown promise as an enabling tool for detecting brain tumours using MRI. The bottom layers of natural photos and medical images are distinct, although both are used in modern applications of pre-trained models. This research presents a strategy for early identification of brain tumours that involves the extraction and concatenation of many characteristics at different levels.Hybrid classification is carried out by using a number of different adaptive methods, and a deep convolutional neural network (CNN) is suggested for feature extraction. In this study, the models were trained using an open-access dataset made accessible on Kaggle. There are a total of 253 MRI scans in the publicly available dataset, of which 140 have been classed as YES and the remaining 113 as NO. In contrast, 90 sample photos were utilised in a different dataset for testing ML models. The gathered photos from the first stage were then synthesised in the second. The dataset began with the elimination of duplicate photos. Second, all the pitch-black areas were cropped out of the pictures. Each image's top, bottom, left, and right contours are determined in this way by looking for the existence of black areas. These four lines were used to determine the cropping of each picture. Therefore, the photos are cropped to exclude the areas beyond these borders. As a result, the cropped photos include the relevant parts of all the originals. Based on the results of the neural network model, 32 characteristics were used to construct a 2-layer stacked classifier. Layer one of the SC model retained three foundational ML algorithms—PCA, ICA, and LDA—while layer two of the stacked classier model used a Logistic Regression (LR) model. Three separate methods are used to get conclusions for each observation/sample in the dataset. The second layer LR model takes the consequences of these calculations as info. The second-layer model was then used to get a definitive end.

2. Objectives

Detecting brain tumors using machine learning algorithms like Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA) is a complex task that involves image processing and classification techniques. Gather a dataset of brain MRI images. These images should include both tumor and non-tumor cases. The quality and quantity of your dataset will significantly impact the performance of your model. Before applying PCA, ICA, and LDA, preprocess the MRI images.

Typical preprocessing steps include resizing, normalizing pixel values, and potentially denoising the images.PCA (Principal Component Analysis) PCA is a dimensionality reduction technique. You can apply PCA to reduce the dimensionality of the MRI images while retaining as much information as possible. This can help in feature extraction.ICA (Independent Component Analysis) ICA is another dimensionality reduction technique that focuses on finding statistically independent components in the data. It can also be used for feature extraction.LDA (Linear Discriminant Analysis)LDA is primarily a classification technique, but it can also be used for feature extraction. LDA seeks to maximize the separation between classes, which can be beneficial in distinguishing tumor and non-tumorcases.After applying PCA, ICA, and LDA, you might want to select a subset of the most relevant features. This can be done using various feature selection methods like mutual information or feature ranking techniques.Build a classification model using the extracted features. Common choices for classifiers include Support Vector Machines (SVM), Random Forest, or deep learning models like Convolutional Neural Networks (CNNs).Evaluate your model's performance using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Make use of cross-validation to ensure that your model is not overfitting the data.

3. Methods

Although many illnesses have been defeated by recent scientific and human intelligence breakthroughs, cancer continues to kill individuals despite these developments. This illness remains a major threat to humankind. One of the most earnest and dangerous sicknesses is disease of the cerebrum.Treatment decisions are based on a number of factors, including the tumor's stage of development, its pathological classification, and the results of the diagnostic testing. A neurologist employing CAD (computer-aided diagnosis) as a supplementary tool for a medical procedure must address the crucial difficulties of analysing, classifying, and identifying brain tumours. In conclusion, this study provides a deep learning and machine learning-based method for efficiently detecting brain tumours in MRI scans.

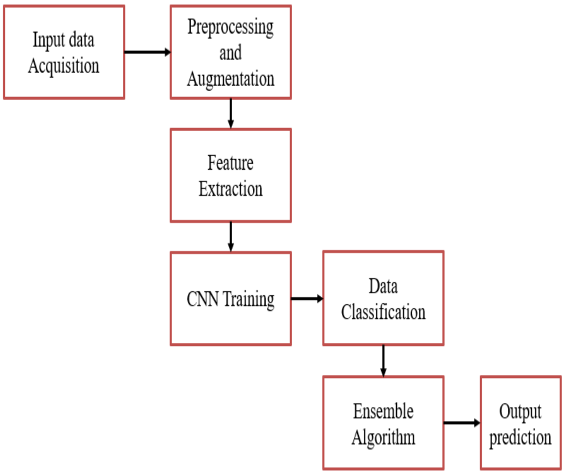

Fig1 : Block Diagram of Proposed Model

Input Data

In this study, the models were trained using an open-access dataset made accessible on Kaggle. There are a total of 253 MRI scans in the publicly available dataset, of which 140 have been classed as YES and the remaining 113 as NO. In contrast, 90 sample photos were utilised in a different dataset for testing ML models.

Data Synthesis

The gathered photos from the first stage were then synthesised in the second. The dataset began with the elimination of duplicate photos. Second, all the pitch-black areas were cropped out of the pictures. Each image's top, bottom, left, and right contours are determined in this way by looking for the existence of black areas. These four lines were used to determine the cropping of each picture. Therefore, the photos are cropped to exclude the areas beyond these borders. As a result, the cropped photos include the relevant parts of all the originals.

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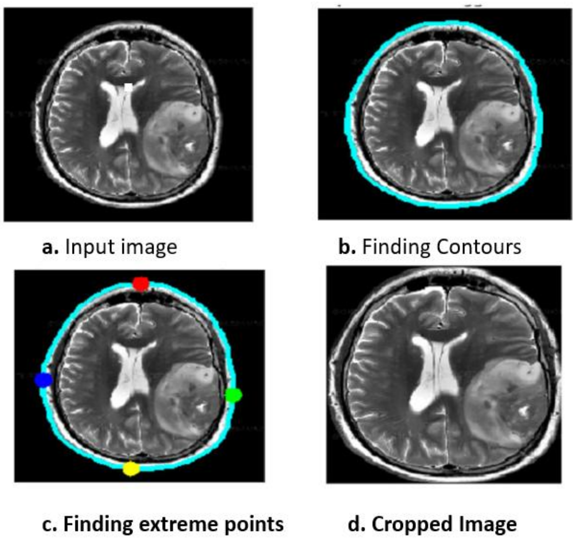

Fig 2: Steps involved in synthesis process

Conventional ML model

CNN, SVM, RF, DT, NB, and KNN are only few of the algorithms considered here; others are based on current efforts in brain tumour classification. Scikit-learn, a Matlab package used in several ML methods, was leveraged in the creation of these models.In the sections that follow, we'll take a closer look at how each algorithm works in practise.

Convolutional Neural Networks

CNN's essential purposes are in the field of picture handling as a result of the secret potential to use the math of the photos.In terms of graph analysis, CNN excels above many other methods. It combines the concepts of spatial or temporal subsampling with shared weights and local receptive fields.

Proposed CNN Model

- For starters, there's the input layer, where the picture characteristics are really sent in.
- Convolutional layer two, with 32 channels for every layer and a 7x7 part size. In a convolutional layer, a channel is applied to the photographs, clearing out pointless parts while defending the critical ones. Anyway, the sigmoid was used as the sanctioning capacity in this stage.
- The third layer is the maximum pooling layer, and its pool size is 44.
- Dropout layer number four, with a dropout pace of half; this layer dispensed with half of the organization's neurons at irregular.
- Fifth, the straighten layer, is the capability that takes the pooled include guide and transforms it into a solitary segment for the completely connected layer to work with.
- The sixth layer is the dense layer, which is completely coupled and receives as input the characteristics from the fifth layer. The activation function for this layer was a sigmoid curve.
- The seventh layer is the output layer, and it predicts the likelihood that a tumour is present in an MRI scan. If the chance of a brain tumour being present in a picture was more than 50%, then the image was classified as showing a brain tumour.

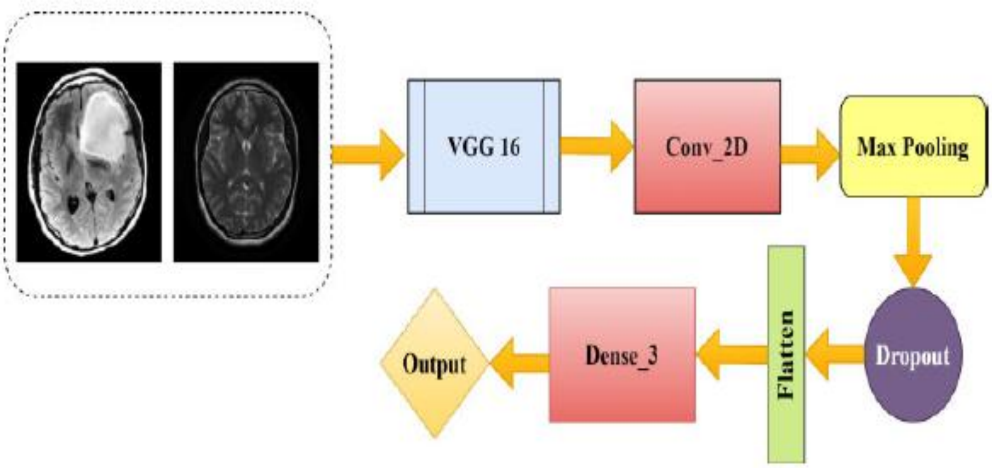

Figure3 : Proposed CNN Model

VGG-16

In their publication "Very Significant Convolutional Associations for Gigantic Extension Picture Affirmation," researchers at the University of Oxford, K. Simonyan and A. Zisserman, presented the VGG16 convolutional brain network model. The model achieves top-5 test accuracy of 92.7% on ImageNet, a dataset of over 14 million images annotated with 1000 classes. It was a well-known model that competed in the 2014 ILSVRC. Moreover, AlexNet is made by replacing the massive part evaluated channels (11 and 5 in the first and second convolutional layer, separately) with a variety of 33 piece estimated directives in a unified fashion. A blueprint for the VGG-16 model is shown.

Hybrid Model Analysis

In their publication "Very Important Convolutional Associations for Immense Degree Picture Affirmation," researchers at the University of Oxford, K. Simonyan and A. Zisserman, presented the VGG16 convolutional brain network model. When tested on ImageNet, a collection of over 14 million images annotated with 1000 classes, the model achieves top-5 accuracy of 92.7%. The model was submitted to ILSVRC-2014 and was considered to be of high quality. The further steps in the creation of AlexNet include replacing large portion evaluated channels (11 and 5 in the first and second convolutional layer, separately) with a number of 33 piece estimated diverts. Model VGG-16's blueprint is described.

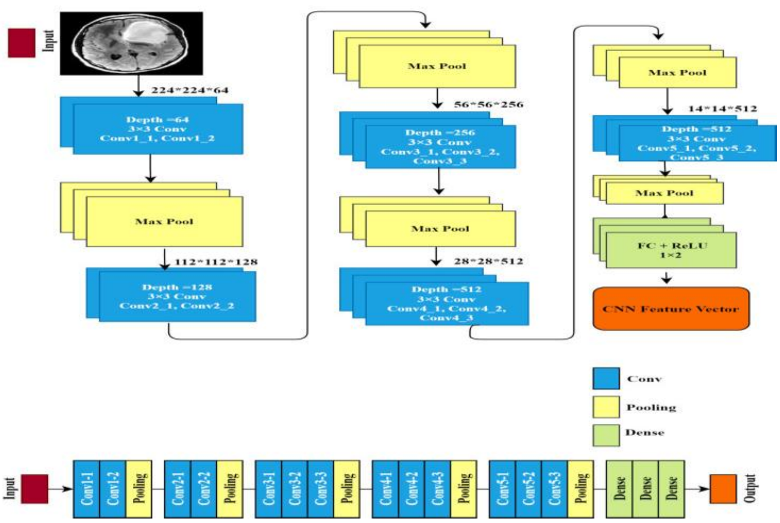

Figure4 : VGG-16 Architecture

Feature Extraction

In this project the methods used for extraction of features are:

i. Principal Component Analysis (PCA)

ii.Linear Discriminant Analysis (LDA)

iii.Independent Component Analysis (ICA)

i. Principal Component Analysis

Principal component analysis (PCA), an eigen value decomposition of the data along the directions of maximum variation in the data, is utilised in this research to extract features. When there is a huge quantity of data, some of which is likely to be irrelevant, PCA may be useful.Principal component basis functions are orthogonal to one another. PCA is often used to classify data and reduce the number of dimensions it has. Exploratory data analysis and predictive modelling both benefit from PCA's usage. To secure lower-layered information while keeping however much of the information's fluctuation as could reasonably be expected, it is frequently utilized for dimensionality decrease by projecting every data of interest onto only the initial not many head parts.

PCA Process of Extraction

Identifying the patterns in data followed by compressing the data by reducing the higher dimensions to the lower dimensions is the objective of PCA. This is done without causing any effects on the data set. In PCA, the data acquired (signal) is of dimensions 8 x 900, each column of which is subtracted using a specific data column. In comparison to each other, covariance examines the degree to which the measurements differ from the mean. The covariance matrix describes the relationship between the pairs of measurements in the data set considered. The covariance is always determined and assessed in relation to the two dimensions. Covariance is calculated by

$$\text{Covariance}\left(c(x,y)\right) = \frac{\sum_{i=1}^{N}(X_i - X)(Y_i - Y)}{n-1}$$

The supplied matrix's covariance is calculated using the aforementioned equation. In this scenario, we identify principle components for all subjects and utilise them in the subsequent classification procedure, reducing the original 14 x 900 matrix to a smaller 14 x 14 matrix. Utilizing PCA the essential parts are found and the highlights are removed from the info information and afterward took care of to CNN and Classifiers.

ii. Linear Discriminant Analysis

To find a straight mix of qualities that portrays or separates at least two classes of items or events, analysts and different scientists frequently go to direct discriminant investigation (LDA), otherwise called typical discriminant examination (NDA) or discriminant capability examination.

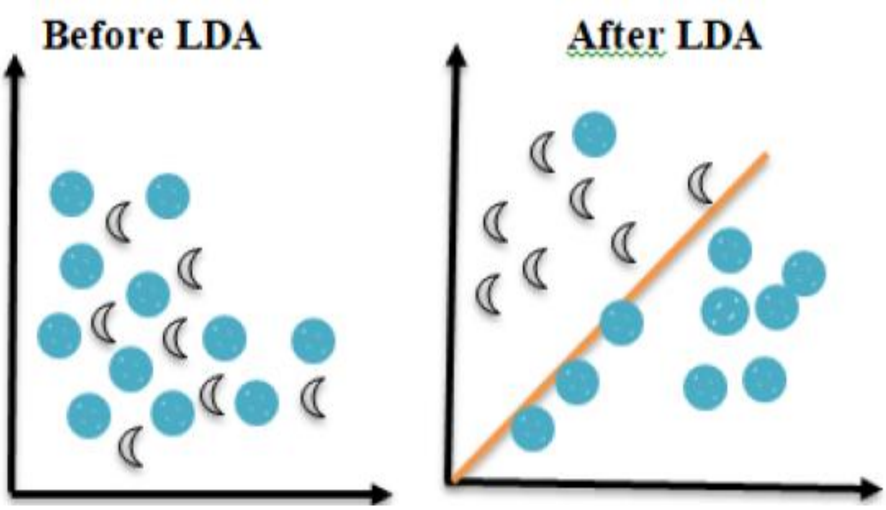

Fig5 : Classification analysis when LDA is used

iii. Independent Component Analysis

Independent component analysis(ICA) is an electronic strategy for disintegrating a multivariate sign into added substance subcomponents in the field of sign handling.To do this, it is assumed that the components are statistically independent non-Gaussian signals. Independent component analysis disentangles a multivariate signal into its component non-Gaussian components. In many cases, the signal that represents sound is the numerical sum of signals from several sources at each instant in time t. The issue then becomes whether or not these sources can be isolated and their contributions to the overall signal evaluated. Blind ICA separation of a mixed-signal yields excellent results when the statistical independence criteria is fulfilled.

Classifiers Stacked

The neural network classification model picked 32 characteristics from which a 2-layer stacked classifier was constructed. Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Independent Component Analysis (ICA) are the three central ML strategies.In the second layer of the stacked classifier model,Strategic Relapse (LR) was utilized rather than the first SC model.The collection includes observations and samples for which three distinct algorithms provide judgements. The second layer LR model is fed the decisions made by these algorithms. The second-layer model was then used to get the ultimateconclusion

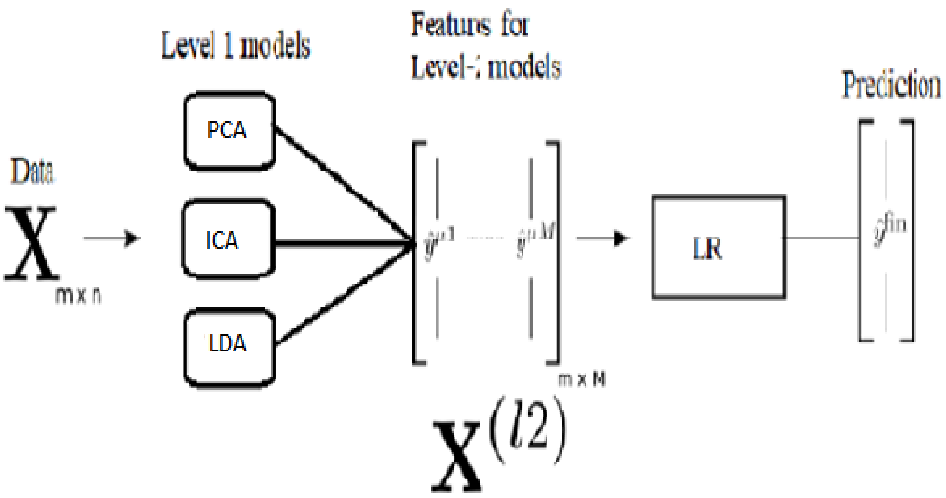

Figure6: Architecture of proposed stacked classifier

Parameters Evaluated

- Recall $= \frac{TP}{TP+FN}$
- F1 Score = (2∗TP)/(2∗TP+FP+FN)
- Precision: $P_e = \frac{TP}{TP+FP}$
- TP- True Positive, FP- False Positive
- TN-True Negative, FN-False Negative

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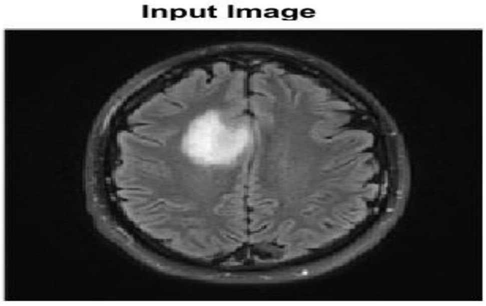
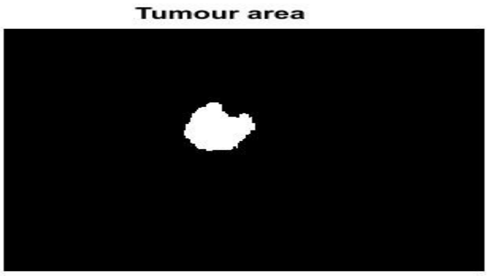
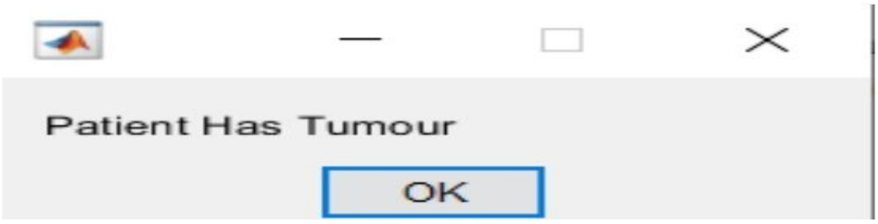
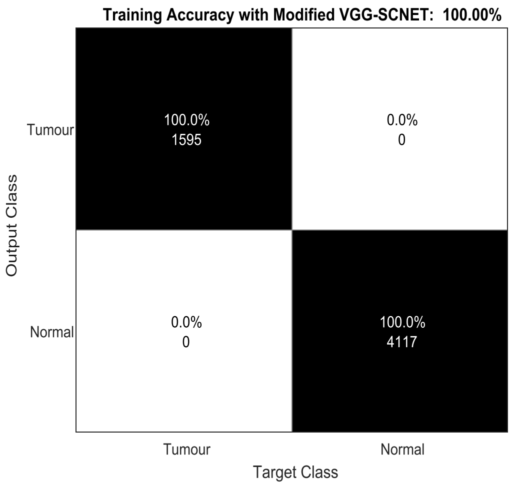
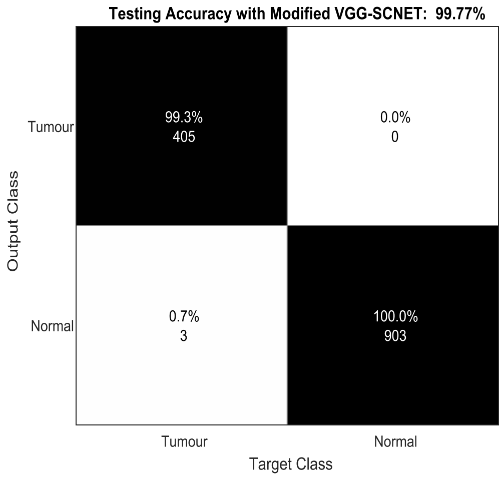
4. Results

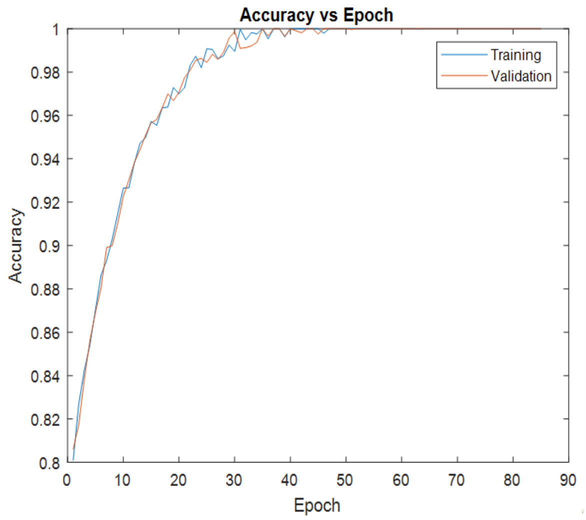












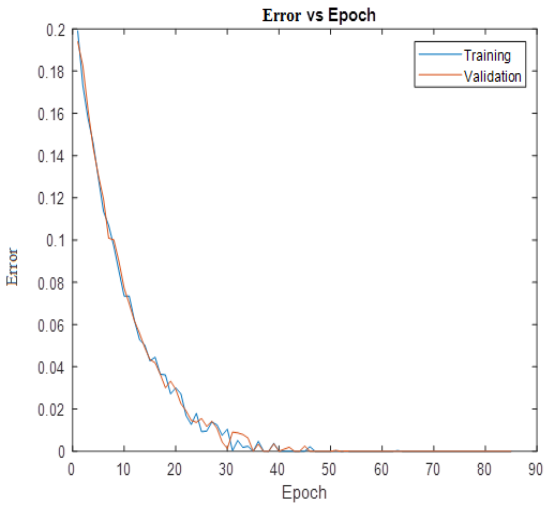


Fig 7: Accuracy plot Fig 8: Error plot

Comparison of results

s.no		Existing method (VGG16 with SVM ,RF, MLP ALGORITHMS)		Proposed method (VGG16 with PCA,ICA,LDA algorithms)	
		Training Data	**Testing data**	**Training data**	**Testing data**
1	Accuracy	100	99.46	100	99.77
2	Recall	100	99.01	100	99.26
3	Precision	100	99.25	100	100
4	F1 score	100	99.13	100	99.63

Table:1 comparison of existing and proposed method

5. Discussion

The need for quick and unprejudiced examination of monstrous volumes of clinical information has prompted an ascent in revenue in X-ray based clinical picture handling for examinations of cerebrum growths. Due to the high mortality rate associated with brain tumors, early diagnosis is essential for effective treatment. Due to the brain's complexity, a manual diagnosis of brain and tumor tissues is labor-intensive and requires an experienced operator. Therefore, in this study, we present the VGG-SCNet, a transfer learning-based SC model that can accurately detect brain tumours from MRI scans. Following feature extraction using PCA, IDA, and LDA, CNN training, and classification with a staked classifier, here. The F1 score accomplished by the recommended marked classifier exhibits the viability of the strategy.

Refrences

[1] Majib, Mohammad Shahjahan and Rahman, Md Mahbubur and Sazzad, TM Shahriar and Khan, Nafiz Imtiaz and Dey, Samrat Kumar, "Vgg-scnet: A vgg net-based deep learning framework for brain tumor detection on mri images", IEEE Access,vol. 9,pp. 116942—116952,2021.

[2] S. Bauer, R. Wiest, L. P. Nolte, and M.Reyes. (2013). A Survey of MRI-BasedMedical Image Analysis for BrainTumour *Studies*. [Online].Available:http://www

[3] R. Leece, J. Xu, Q. T. Ostrom, Y. Chen,C. Kruchko, and J. S. Barnholtz-Sloan,``Global incidence of malignant brain and other central nervous system tumorsby histology, 2003_2007,'' *Neuro-Oncology*, vol. 19, no. 11, pp.1553_1564, Oct. 2017.

[4] T. A. Dolecek, J. M. Propp, N. E. Stroup and C. Kruchko, ``CBTRUS statistical report: Primary brain and central nervous system tumours diagnosed in the United States in 2005_2009,'' *Neuro. Oncol.*, vol. 14, no. 5, pp. v1_v49, 2012.

[5] D. N. Louis, A. Perry, G. Reifenberger, A. von Deimling, D. Figarella-Branger, W. K. Cavenee, H. Ohgaki, O. D. Wiestler, P. Kleihues, and D. W. Ellison ``The 2016 World Health Organization classification of tumours of the central nervous system: A summary,'' *Acta Neuropathol.*, vol. 131, no. 6, pp. 803_820, 2016.

[6] R. Stupp *et al.*, ``Radiotherapy plus concomitant and adjuvant temo- zolomide for glioblastoma,'' *New England J. Med.*, vol. 352, no. 10, pp. 987_996, 2005.

[7] S. Bakas *et al.*, ``Identifying the best machine learning algorithms for brain tumor segmentation, progression assessment, and overall survival prediction in the BRATS challenge,'' 2018, *arXiv:1811.02629*. [Online]. Available: https://arxiv.org/abs/1811.02629

[8] B. H. Menze, K. van Leemput, D. Lashkari, M.-A. Weber, N. Ayache, and P. Golland, ``A generative model for brain tumor segmentation in multi-modal images,'' in *Proc. Int. Conf. Med. Image Comput. Comput.-Assist.Intervent.*, 2010, pp. 151_159.

[9] S. Bakas, H. Akbari, A. Sotiras, M. Bilello, M. Rozycki, J. S. Kirby, J. B. Freymann, K. Farahani, and C. Davatzikos, ``Advancing the cancer genome atlas glioma MRI collections with expert segmentation labels and radiomic features,'' *Sci. Data*, vol. 4, no. 1, Dec. 2017, Art. no. 170117.

[10] S. Bakas *et al.*, ``Segmentation labels and radiomic features for the pre- operative scans of the TCGA-LGG collection,'' *Cancer Imag. Arch.*, vol. 286, 2017.

[11] S. Bakas, H. Akbari, A. Sotiras, M. Bilello, M. Rozycki, J. Kirby, J. Freymann, K. Farahani, and C. Davatzikos ``Segmentation labels and radiomic features for the pre-operative scans of the TCGA-GBM collection. The cancer imaging archive,'' *Nat. Sci. Data*, vol. 4, 2017, Art. no. 170117.

[12] B. H. Menze *et al.*, ``The multimodal brain tumor image segmentation benchmark (BRATS),'' *IEEE Trans. Med. Imag.*, vol. 34, no. 10, pp. 1993_2024, Oct. 2015.

[13] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, ``Brain tumor segmentation using convolutional neural networks in MRI images,'' *IEEE Trans. Med.Imag.*, vol. 35, no. 5, pp. 1240_1251, May 2016.

[14] M. B. Naceur, R. Saouli, M. Akil, and R. Kachouri, ``Fully automatic brain tumor segmentation using end-to-end incremental deep neural net- works in MRI images,'' *Comput. Methods Programs Biomed.*, vol. 166, pp. 39_49, Nov. 2018.

[15] M. Goetz, C. Weber, F. Binczyk, J. Polanska, R. Tarnawski, B. Bobek-Billewicz, U. Koethe, J. Kleesiek, B. Stieltjes, and K. H. Maier-Hein, ``DALSA: Domain adaptation for supervised learning from sparsely annotated MR images,'' *IEEE Trans. Med. Imag.*, vol. 35, no. 1, pp. 184_196, Jan. 2016.

[16] K. Farahani, B. Menze, and M. Reyes. (2014). *Brats 2014 Challenge Manuscripts (2014)*. [Online]. Available: http//www. braintumoursegmentation.org

[17] P. Mukherjee and A. Mukherjee, ``Advanced processing techniques and secure architecture for sensor networks in ubiquitous healthcare systems,'' in *Sensors for Health Monitoring*. Amsterdam, The Netherlands: Elsevier, 2019, pp. 3_29.

[18] W. Chen, Y. Li, and C. Li, ``A visual detection method for foreign objects in power lines based on mask R-CNN,'' *Int. J. Ambient Comput. Intell.*, vol. 11, no. 1, pp. 34_47, Jan. 2020.

[19] P. C. Burger, E. R. Heinz, T. Shibata, and P. Kleihues, ``Topographic anatomy and CT correlations in the untreated glioblastoma multiforme,'' *J. Neurosurgery*, vol. 68, no. 5, pp. 698_704, May 1988.

[20] F. Raschke, T. R. Barrick, T. L. Jones, G. Yang, X. Ye, and F. A. Howe,``Tissue-type mapping of gliomas,'' *NeuroImage, Clin.*, vol. 21, 2019, Art. no. 101648.

[21] M. Soltaninejad*et al.*, ``Brain tumour grading in different MRI protocols using SVM on statistical features,'' Med. Image Understand. Anal., Royal Holloway, Egham, U.K., Tech. Rep., 2014, pp. 259_264.