Intelligent Supervised Machine Learning-Deep Learning Driven Severity Evaluation and Classification of Brain Tumor Using CNN-SVM

Bhagyalaxmi B S[1], Yashodha H R[2], Ashwini M S[3]

[1]Senior Scale Lecturer, Department of Computer Science & Engineering, Government Polytechnic for Women, Ramanagara
[2]Lecturer, Department of Computer Science & Engineering, Government residential women's polytechnic, Shivamogga
[3]Senior Scale Lecturer, Department of Computer Science & Engineering, Government Polytechnic, Channapatna

Abstract
Brain tumours are among the tenth most common diseases causing the death worldwide, up to 80% and 90% of all primary cancers of the central nervous system. Because of increase in the tumour diseases globally, it becomes necessary to predict the brain tumours in the initial stages only. The survival rate depends on the early diagnosis and efficient treatment. The risk of death is significantly increased when brain tumours are not detected in a timely manner. However, radiologists face many difficulties due to the complex and varied nature of tumour cells, which makes manual processing of magnetic resonance imaging (MRI) scans difficult which is time-consuming. Deep Neural Network learning (DL) and Intelligent Machine Learning (ML) algorithms have become promising technologies in diagnosing medical images, allowing for the automated extraction of relevant patterns and features from MRI data reports to improve tumour diagnosis with fast and accuracy results. The intricacy and unpredictability of brain tumour characteristics can be addressed by these technologies, which could enhance the diagnosis process. Various Deep Neural Network and Intelligent Machine Learning Networks such as VGG19 net, Inception, U-net, RNN, Bi-LSTM, Hybrid model, CNN, Logistic Regression, RF, Decision tress, hybrid models, have been used to extract the expected features from MRI for the early prediction of the brain tumours. This article gives the severity analysis of brain tumours using the MRI imaging taken from the FigShare datasets and BRATs datasets. The CNN model gives the more accuracy compared to the SVM model with 93% and 86% respectively.

Keywords: Deep Learning, Machine Learning, SVM, CNN, Hybrid Model

1. Introduction

Diagnostic imaging in healthcare has been transformed by artificial intelligence (AI), which combines machine learning, deep learning advanced algorithms to improve the analysis of medical images, such as CT, MRI, and X-ray scans. AI changes the diagnostic process, allowing for a more precise and effective method of disease identification, rather than just automating jobs. This technique represents a major advancement in diagnostic imaging analysis and application [1]. Brain tumours are a major global health concern, where the death rate is increasing drastically. The two main categories for these malignancies are primary and secondary stages. Cancer cells that move to the brain from other organs, like the kidneys, breasts, skin, lungs, or thyroid, are the source of secondary brain tumours, whereas primary brain tumour’s start and grow inside the brain itself. Patients with malignant secondary tumours have a less chance of survival [2,3]. On the other hand, initial cancers frequently present as benign at first, and survival rates can be considerably increased by early detection and precise diagnosis.

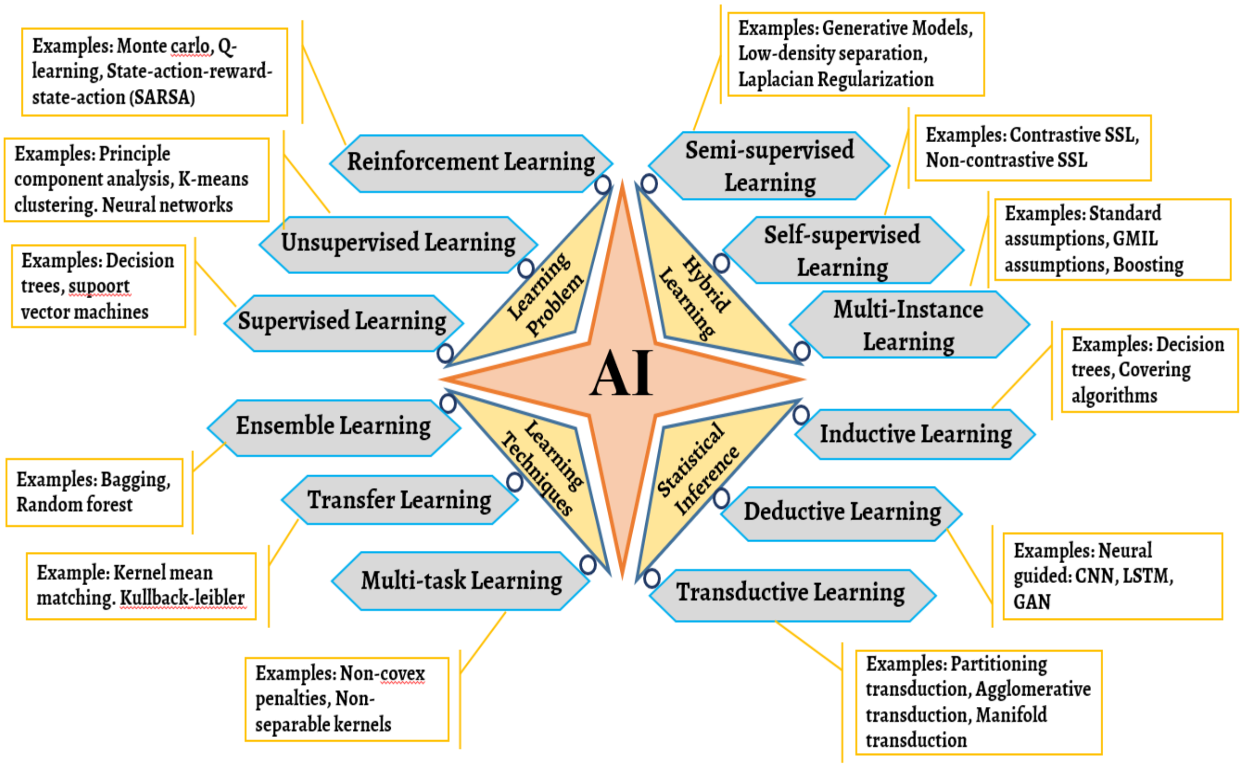
A tumour in the brain are referred as abnormal growth of extra cells inside the brain. These cells may be non-cancerous (benign) or cancerous (malignant) [5]. The cancerous cells may originate from the root of the brain and spread to other parts of the body in the severe cases, which leads to a painful symptom like headaches, seizures, vision impairments, nausea, and also malfunctioning of the brain. The brain tumour is very dangerous and life threatening disease which may be affected to anyone irrespective of age and genders. This is due to the modern life style, use of electronic gadgets like mobile phones, long term use of computer systems, and other similar technologies. The brain controls the many life processes such as functioning of sense organs, emotions, memory. The small gland called in pituitary gland controls the other glands of the human body. Thus malfunctioning of the brain leads to many other diseases in the human body. Hence it became necessary to predict the brain tumour in the early stages. The various features such as tumour shape, size, texture, sharpness scanned by MRI images are used to predict the brain tumour. Many existing manual systems to predict the brain tumour is time consuming, and few techniques using grayscale values leads to poor classification of brain tumour. An essential part in the brain that controls emotions, memory, and movement is the grey matter of the central nervous system. Because unique processes are carried out by different parts of the brain, grey matter is essential to human life. Brain scans have been analyzed using sophisticated image processing techniques. Gliomas are a class of tumour that include, among other things, chordomas, acoustic neuromas, astrocytoma's, and CNS lymphomas. Even while each type may have distinct symptoms, some, including headaches, are shared by all of them. A complete examination of brain imaging is therefore necessary for an appropriate diagnosis, which cannot be made based only on symptoms.

A vital diagnostic technique called the magnetic resonance imaging (MRI) provides images with significant contrast that are particularly helpful in detecting and evaluating neurological disorders such multiple sclerosis, epilepsy, and brain tumours [6]. Because it can provide detailed images without using radiation, MRI is a non-invasive approach that is safer and more effective than other imaging methods like CT scans [7]. It is essential for identifying, classifying, and dividing brain tutors into benign and malignant categories [8,9]. Because of its exceptional spatial resolution, MRI is frequently the preferred imaging modality and is essential for neuroscientific research, tumour diagnosis, and treatment planning [9]. Although MRI has many benefits, the process of identifying and categorizing brain tumours is laborious and necessitates sophisticated computational techniques to increase precision and effectiveness. In this area, deep learning has become a potent instrument that allows for automatic tumour segmentation and detection straight from unprocessed images [10]. These approaches, however, have drawbacks, including a lack of labeled datasets and the high expense of expert annotation. By making tasks like picture identification, classification, and visual categorization easier, recent developments in deep transfer learning have demonstrated promise in overcoming these constraints.

1.1 Importance of Intelligent Machine Learning and Neural Deep Learning Techniques in analysis of the severity and stages of brain tumour

Machine Learning analysis the sample data sets using the statistical and mathematical models, and also the ML models learns any pattern without using much programming. Arthur Samuel initially introduced the idea in 1959, highlighting how robots may learn from experience by illustrating its potential in gaming and recognition of patterns.

Figure 1: Various AI Algorithms used in Medical Field



The Machine learning algorithms are generally categorized into supervised, unsupervised and reinforcement learning. Further, based on the various learning approaches, the ML algorithms can be divided into various sub-divisions as shown in the Figure [1]. Using Logistic Regression based model sigmoid function applied in prediction of brain tomor gives the best result analysis [11]. Many studies have demonstrated that Intelligent ML and DL algorithms have efficiently with high accuracy have analysed and predicted the brain tomor. Algorithms like ANN, boosted logistic regression, SVM, RF, K-means, has outperformed in the prediction of brain tumour diseases with the accuracy of 97.4% [12]. Deep Learning algorithms like CNN frameworks such as VGG16, VGG19, Inception model [13], have achieved more accuracy in the prediction of brain tumour classification. The experiment was carried out using publicly available three image datasets: BraTs2015, BraTs2017, and BraTs2018, and achieved 97.8%, 96.9%, and 92.5% accuracy, respectively.

1.2 Motivation Behind Research

This research is driven by the crucial require to increase the precision and effectiveness of categorizing the level of severity of brain tumours, since current approaches have significant drawbacks, including challenging manual interpretation, high error rates because of injury variability, limited generalizations of deep learning methodologies, and a lack of labeled datasets. In order to improve diagnosis, the process of segmentation and illness severity classification, and eventually help with better treatment planning and patient outcomes, an advanced, automated system utilizing deep learning and hybrid optimization techniques is required.

The remaining part of this research article are categorized as Section 2 specifies the Deep Learning techniques and Intelligent ML approaches applied in the analysis and prediction of the brain tumour. Section 3 explores the classification of severity. Section 4 discusses on the Deep Neural Networks model algorithms to predict and analyze the severity of the brain tumour, and finally the conclusion of the presented work in section 5.

2. Review on the Exiting works on Prediction and Analysis of Brain Tumor

Numerous studies have been done on the prediction of the brain tumour by applying Intelligent Machine Learning and Deep Learning Neural Network techniques. The traditional approaches in manual feature extraction for brain tumour prediction, for instance, Islam et al. [14] in their proposed framework used a median extraction for pre-processing, for feature extraction of the tumour the author applied super-pixel and PCA by using the K-means clustering for the process of segmentation and prediction. The drawback of the work is, time consuming in the prediction of illness classification with low accuracy.

Brain tomor identification has been transformed by deep learning techniques, which offer better generalization than conventional approaches and do away with the requirement for manual feature extraction using convolutional filters. With a 96% accuracy rate, Lu et al. [15] used MobileNetV2 for feature extraction and a random vector functional-link net technique. After testing several pre-trained CNNs, Talo et al. [16] used transfer learning with ResNet and achieved above 95% accuracy in binary classification. Later, [17] evaluated ResNet50 and found that it achieved 95.23% accuracy. A multi-step method that included fuzzy logic, the sine cosine segmentation technique, and a CNN model was presented by Kumar and Mankame [18] and achieved 96.23% accuracy. With 98.5% accuracy, Raja and Siva [19] created a deep auto-encoder model for glioma classification that included Bayesian clustering for pre-processing and segmentation and median filtering. Using a customized CNN with five convolutional layers and pre-processing with Canny edge detection, Devi and Gomathi [20] achieved 91% accuracy. These developments demonstrate how well deep learning works to improve the accuracy and effectiveness of brain tumour identification.

Tandel et. al. [4] in their proposed model predicted the brain tumour by using the transfer learning AI based framework, extracting the features from the MRI images. The author used multi-classification algorithm such as Support Vector Machine, Navies' Base, Logistic Regression, CNN and tested on five to six datasets. Though the proposed model gave good results but was unable to give best results on huge datasets.

Javaria Amin et al. [21] proposed a fusion model which combined T1, T2, T1C, and flair MRI images to predict the brain tumour. The proposed method applied daubenchies wavelet curves and Discrete Wavelet Transform in their fusion model, and to filter the unwanted attributes and to reduce the noise author used Partial Differential Diffusion Filter. Tumour classification and segmentation was achieved through CNN and global threshoding. But the framework could not give the results on enhanced imaging techniques such as CT scans and PET scans.

Arun Kumar et al. [22] in their work developed a brain tissue segmentation approach to predict and analyse the brain tumour classification using MRI imaging, which incorporated the images segmentation, filtering of non ROI based images on the HOG and texture. To recognise the ROI, the author applied Artificial Neural Networks with histogram for object analysis. In spite of all this techniques, the proposed model struggled with segmenting the large tumours inside the brain.

To address the challenges in existing methods, the Scale Fused Bi-LSTM Attention Model (SFBAM) is proposed for classifying the severity of brain tumours using MRI. The SFBAM architecture incorporates multi-scale feature extraction and assigns appropriate weights to features using an attention mechanism, enabling accurate classification. Additionally, the Spark model enhances processing efficiency by utilizing slave node servers for parallel computation. Techniques like ROI extraction and Laplacian filtering effectively reduce noise in MRI images, improving image quality for analysis. The SFBAM proves to be highly effective in analyzing MRI images and achieving optimal classification results, outperforming traditional methods. This architecture not only addresses the challenges in medical imaging but also offers a robust solution for network systems by distinguishing between attacks and normal traffic with high precision, thereby improving intrusion detection systems and overall network security.

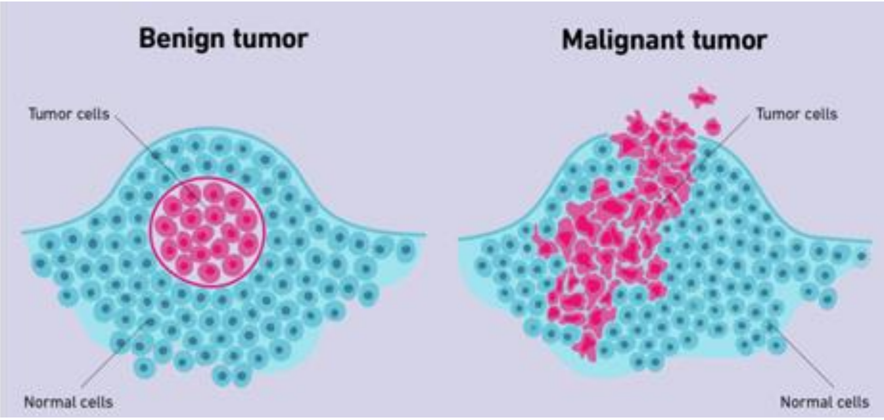
3. Methodology

Convolutional Neural Networks (CNNs) are well-performing supervised deep neural network learning techniques that have made major strides in the processing of images. Three main layers are usually present in these networks: convolutional neural networks, combining networks, and fully linked layers. The convolutional layers create several feature maps by applying different kernels to the input image. By sharing weights, this procedure drastically lowers the number of parameters and enables the network to discover the connections among nearby pixels via local inter-connectivity. The algorithm transforms the input data to add an input channel dimension, guaranteeing compatibility with convolutional models, in order to prepare MRI data for brain tumour prediction. Image-Data-Generator is used for data augmentation, normalizing pixel values to a [0, 1] range and applying transformations like shear, zoom, and horizontal flips to increase the training dataset's diversity. By simulating changes in the data, these augmentations strengthen the model's resistance to alterations in the input images. Because the augmented data is produced in batches, memory utilization is minimized and training and validation are made more effective. The model can successfully learn pertinent features for precise brain tumour classification with preprocessing approach.

Description of the datasets:

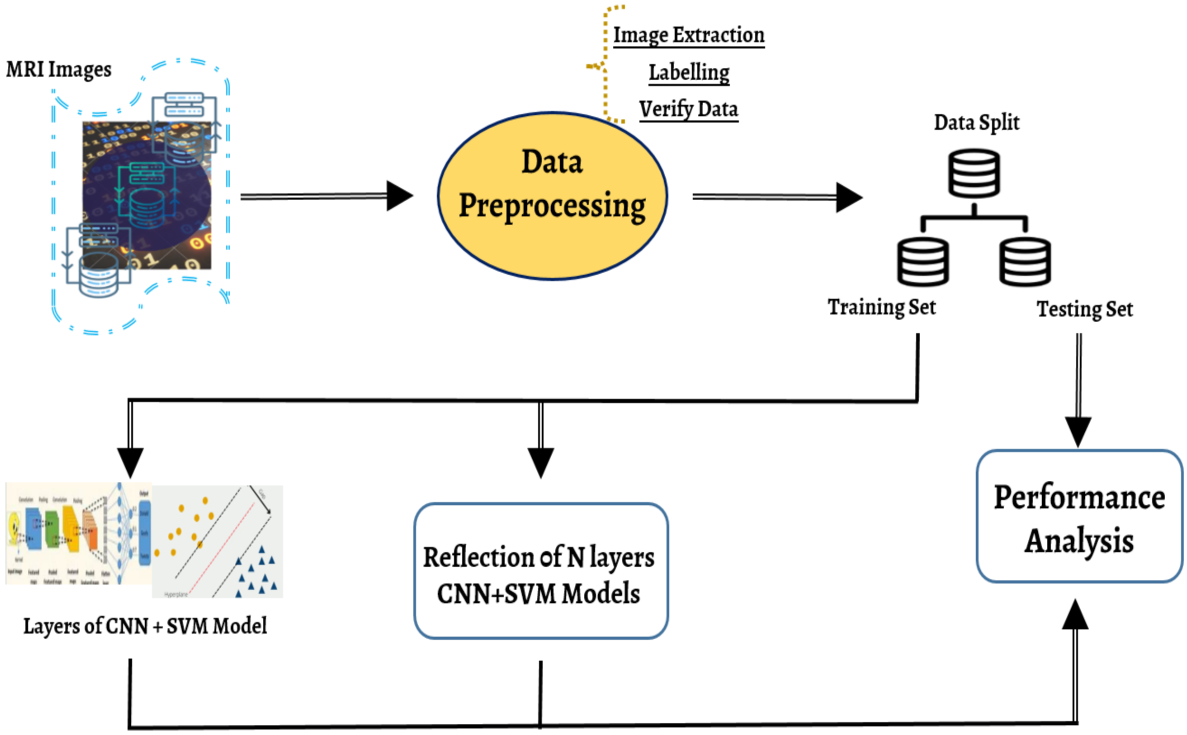
The train the proposed model the datasets are taken from the FigShare Datasets and BRATS 2020. Various images with the several severity is being found in the BRATs 2020 [23]. These datasets contain the MRI brain images which is extracted from the four modalities, T1, T2, T1C and FLAIR. The FigShare [24] datasets contain T2-weighted images from more than 200 patients, that are analysed by taking pituitary tumours, and Glioma.

Figure 2: Classification of Brain Tumor by Extracting Features from MRI



CNN categorizes brain tumor images into four groups: hypothalamic tumor, meningioma tumor, glioblastoma tumor, and no tumor. In order to extract visual information like as the edges, textures in particular, forms, and intensities patterns, it applies filters to the input images using convolutional layers. Low-level features, including tumor boundaries, are captured by these layers, which then advance to high-level features, like textures and morphologies unique to a tumor. In order to minimize computational effort and preserve important information, pooling layers shrink the spatial dimensions of feature maps. Each class's probabilities are produced by the final Softmax layer after fully linked layers have mapped the extracted features to tumor classes. Images are given into the model, which determines the most likely tumor type, after being shrunk to 224x224 and normalized. The approach is understandable and useful for diagnostic applications because the retrieved features allow for precise tumor type discrimination and visualizations confirm the model's predictions. The proposed architecture is shown in the diagram below

Figure 3: Proposed SVM-CNN Model



The proposed CNN model uses a collection of images from the "glioma_tumor" dataset to display the model's predictions. Every image is initially read and pre-processed to satisfy the CNN model's input specifications. This includes scaling each image to 224x224 pixels and normalizing pixel values to fall between 0 and 1. To extract features like edges, textures, and forms, the images taken from the MRI report are then run through a CNN, which has layers like convolutional, pooling, and fully connected layers. While pooling layers minimize the spatial dimensions and increase the computational efficiency of the model.

In order to classify tumors using SVM, MRI images are analyzed to identify tumor locations using an attribute vector that contains statistical, Texton, and Karhunen-Loeve Transform-based features. By classifying these retrieved features using SVM, tumorous areas are identified based on their attributes. SVM is a potent binary classification method whose main goal is to identify the best hyperplane for dividing the data into two different classes. Many binary SVMs are frequently combined for multiclass classification. An output neuron, a hidden layer, and an input layer make up the SVM model. An input and its corresponding class label serve as representations of each data instance during training. Performance is enhanced by optimizing the weight vector and bias that define the decision hyperplane in order to maximize the margin between the classes as shown in the equation below in equation1.

$$w.x + b = 0 \qquad (1)$$

To classify training and testing data, the hyperplane is modified and modelled as given in equation 2.

$$f(x) = sign(w.x + b) \qquad (2)$$

When controlling the kernel function, the previous function is written as in the equation 3.

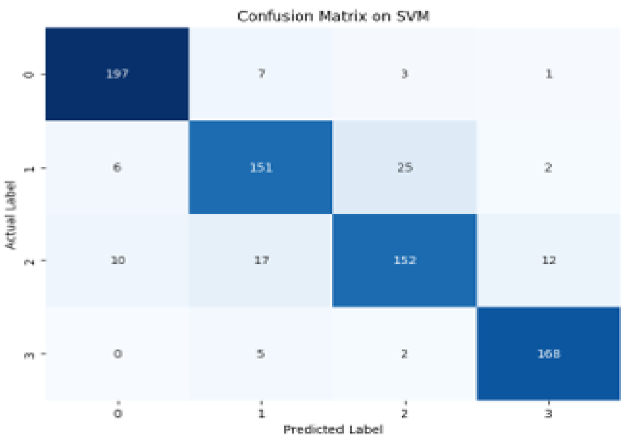
$$f(x) = sign(\sum_{i=1}^{N} a_i y_i k(x_i, x + b)) \qquad (3)$$

where N represents the total no. of training datasets, xi is the input data for training the model and yi is the corresponding label. The kernel function $k(x_i, x+b)$is used to map the input vector to higher dimensional space To compute the coefficients a_i and b, two constraints are applied during the optimization process. These constraints help in finding the optimal decision boundary that maximizes the margin between the classes, ensuring accurate classification.

4. Results and Discussions

The datasets from which are the MRI scan images are fed to train the both the models. The training and the testing datasets are taken in the proportion 80:20 respectively. The Efficiency of both the algorithms are shown in the diagram below. From evaluation metrics it is predicted that CNN outperforms the best with the accuracy of 93% in the prediction of brain tumour compared to SVM model. The analysis of the proposed model is done on the evaluation metrics such as precision, recall, F1 score with the confusion matrix.

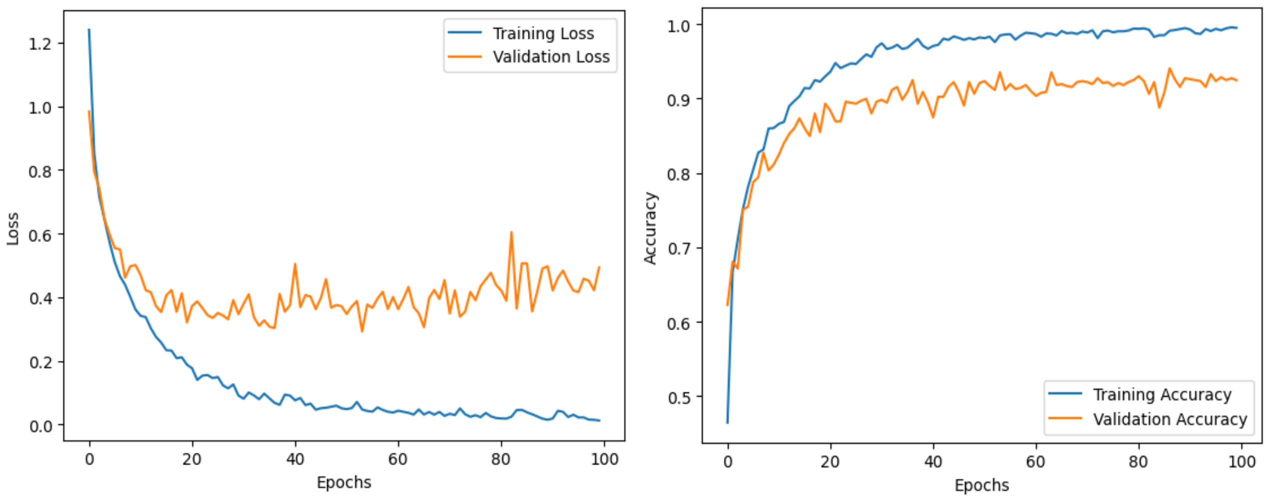
Figure 4: Analysis of Brain Tumour using SVM



SVM Classification Report:

	precision	recall	f1-score	support
0	0.92	0.95	0.94	208
1	0.84	0.82	0.83	184
2	0.84	0.80	0.82	191
3	0.92	0.96	0.94	175
accuracy			0.88	758
macro avg	0.88	0.88	0.88	758
weighted avg	0.88	0.88	0.88	758

Figure 5: Analysis of Brain Tumour using CNN



```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 222, 222, 32)      320

 max_pooling2d (MaxPooling2  (None, 111, 111, 32)      0
 D)

 conv2d_1 (Conv2D)           (None, 109, 109, 64)      18496

 max_pooling2d_1 (MaxPoolin  (None, 54, 54, 64)        0
 g2D)

 flatten (Flatten)           (None, 186624)            0

 dense (Dense)               (None, 128)               23888000

 dense_1 (Dense)             (None, 4)                 516

=================================================================
Total params: 23907332 (91.20 MB)
Trainable params: 23907332 (91.20 MB)
Non-trainable params: 0 (0.00 Byte)
```

```
95/95 [==============================] - 12s 125ms/step - loss: 0.0173 - accuracy: 0.9941
Accuracy on Train Data: 0.9940593838691711
24/24 [==============================] - 3s 113ms/step - loss: 0.5106 - accuracy: 0.9301
Accuracy on Test Data: 0.9300791621208191
```

5. Conclusion

The proposed SVM-CNN based model is devised for the prediction of the severity of the brain tumour, by collecting the MRI imaging datasets from the FigShare and BRATs 2020. The mater node and the slave node are used to perform severity classification of the brain tumour. The image generated after pre-processing is given for the segmentation. The features extraction is performed based on the mean, entropy, kurtosis and the variance, and these images after this phase is trained and tested on the CNN-SVM based model. The CNN outperforms with the efficiency of 93%, over the SVM model which gives the accuracy of 86%. Further the work can be extended by using the advanced integrated model with the advanced datasets for the improvement of the performance in the analysis.

References

1. Wenderott, K., Gambashidze, N., & Weigl, M. (2022). Integration of Artificial Intelligence Into Sociotechnical Work Systems—Effects of Artificial Intelligence Solutions in Medical Imaging on Clinical Efficiency: Protocol for a Systematic Literature Review. In JMIR Research Protocols (Vol. 11, Issue 12). https://doi.org/10.2196/40485
2. Dimililer, K., & Ilhan, A. (2016). Effect of Image Enhancement on MRI Brain Images with Neural Networks. Procedia Computer Science, 102. https://doi.org/10.1016/j.procs.2016.09.367
3. Franchino, F., Rudà, R., & Soffietti, R. (2018). Mechanisms and therapy for cancer metastasis to the brain. In Frontiers in Oncology (Vol. 8, Issue MAY). https://doi.org/10.3389/fonc.2018.00161
4. Ben Ahmed, K., Hall, L. O., Goldgof, D. B., & Gatenby, R. (2022). Ensembles of Convolutional Neural Networks for Survival Time Estimation of High-Grade Glioma Patients from Multimodal MRI. Diagnostics, 12(2). https://doi.org/10.3390/diagnostics12020345
5. Kumar, S., & Mankame, D. P. (2020). Optimization driven Deep Convolution Neural Network for brain tumor classification. Biocybernetics and Biomedical Engineering, 40(3). https://doi.org/10.1016/j.bbe.2020.05.009

6. Michael Mahesh, K., & Arokia Renjit, J. (2020). Multiclassifier for severity-level categorization of glioma tumors using multimodal magnetic resonance imaging brain images. International Journal of Imaging Systems and Technology, 30(1). https://doi.org/10.1002/ima.22357
7. Shi, F., Yap, P. T., Fan, Y., Gilmore, J. H., Lin, W., & Shen, D. (2010). Construction of multi-region-multi-reference atlases for neonatal brain MRI segmentation. NeuroImage, 51(2). https://doi.org/10.1016/j.neuroimage.2010.02.025
8. Avinash Gopal. (2020). Hybrid classifier: Brain Tumor Classification and Segmentation using Genetic-based Grey Wolf optimization. Multimedia Research, 3(2). https://doi.org/10.46253/j.mr.v3i2.a1
9. Tong, J., Zhao, Y., Zhang, P., Chen, L., & Jiang, L. (2019). MRI brain tumor segmentation based on texture features and kernel sparse coding. Biomedical Signal Processing and Control, 47. https://doi.org/10.1016/j.bspc.2018.06.001
10. Operto, F. F., Pastorino, G. M. G., Stellato, M., Morcaldi, L., Vetri, L., Carotenuto, M., Viggiano, A., & Coppola, G. (2020). Facial emotion recognition in children and adolescents with specific learning disorder. Brain Sciences, 10(8). https://doi.org/10.3390/brainsci10080473
11. Nazir, M., Shakil, S., & Khurshid, K. (2021). Role of deep learning in brain tumor detection and classification (2015 to 2020): A review. Computerized Medical Imaging and Graphics, 91. https://doi.org/10.1016/j.compmedimag.2021.101940
12. G.Gokulkumari. (2020). Classification of Brain Tumor using Manta Ray Foraging Optimization-based DeepCNN Classifier. Multimedia Research, 3(4). https://doi.org/10.46253/j.mr.v3i4.a4
13. Amin, J., Sharif, M., Raza, M., & Yasmin, M. (2024). Detection of Brain Tumor based on Features Fusion and Machine Learning. Journal of Ambient Intelligence and Humanized Computing, 15(1). https://doi.org/10.1007/s12652-018-1092-9
14. Islam, M. K., Ali, M. S., Miah, M. S., Rahman, M. M., Alam, M. S., & Hossain, M. A. (2021). Brain tumor detection in MR image using superpixels, principal component analysis and template based K-means clustering algorithm. Machine Learning with Applications, 5. https://doi.org/10.1016/j.mlwa.2021.100044
15. Lu, S. Y., Wang, S. H., & Zhang, Y. D. (2020). A classification method for brain MRI via MobileNet and feedforward network with random weights. Pattern Recognition Letters, 140. https://doi.org/10.1016/j.patrec.2020.10.017
16. Talo, M., Baloglu, U. B., Yıldırım, Ö., & Rajendra Acharya, U. (2019). Application of deep transfer learning for automated brain abnormality classification using MR images. Cognitive Systems Research, 54. https://doi.org/10.1016/j.cogsys.2018.12.007
17. Talo, M., Yildirim, O., Baloglu, U. B., Aydin, G., & Acharya, U. R. (2019). Convolutional neural networks for multi-class brain disease detection using MRI images. Computerized Medical Imaging and Graphics, 78. https://doi.org/10.1016/j.compmedimag.2019.101673
18. Kanchanamala, P., Revathi, K. G., & Ananth, M. B. J. (2023). Optimization-enabled hybrid deep learning for brain tumor detection and classification from MRI. Biomedical Signal Processing and Control, 84. https://doi.org/10.1016/j.bspc.2023.104955
19. Siva Raja, P. M., & rani, A. V. (2020). Brain tumor classification using a hybrid deep autoencoder with Bayesian fuzzy clustering-based segmentation approach. Biocybernetics and Biomedical Engineering, 40(1). https://doi.org/10.1016/j.bbe.2020.01.006
20. Devi, K. U., & Gomathi, R. (2023). Retraction Note to: Brain tumour classification using saliency driven nonlinear diffusion and deep learning with convolutional neural networks (CNN). Journal of Ambient Intelligence and Humanized Computing, 14(S1). https://doi.org/10.1007/s12652-022-04193-1
21. Kader, I. A. El, Xu, G., Shuai, Z., Saminu, S., Javaid, I., & Ahmad, I. S. (2021). Differential deep convolutional neural network model for brain tumor classification. Brain Sciences, 11(3).

https://doi.org/10.3390/brainsci11030352
22. Arunkumar, N., Mohammed, M. A., Mostafa, S. A., Ibrahim, D. A., Rodrigues, J. J. P. C., & de Albuquerque, V. H. C. (2020). Fully automatic model-based segmentation and classification approach for MRI brain tumor using artificial neural networks. Concurrency and Computation: Practice and Experience, 32(1). https://doi.org/10.1002/cpe.4962
23. BRATS 2018 dataset taken from"https://wiki.cancerimagingarchive.net/pages/ viewpage.action?pageId=37224922", accessed on September 2020.
24. Brain tumor dataset from, "https://figshare.com/articles/dataset/brain_tumor_ dataset/1512427", accessed on December 2020.