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Brain Tumour Detection using Sequential Recurrent Neural Network through Optimal Two Phase Selected Features

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Abstract: - In human body, the brain is a complex organ with billions of cells that controls the overall activities of our body. The abnormal and uncontrolled multiplication of these cells leads to Brain tumour which is one of the most dangerous and aggressive second leading diseases in human beings around the world. Many Machine Learning algorithms are used with different classifiers such as Discrete Wavelet Transform, Support Vector Machine, Principal Component Analysis, etc., on Magnetic Resonance (MR) images to segment and classify tumour types. These methods are used only to predict whether the patient has brain tumour or not and also never consider the morphology and histological nature of brain tumour types. This method provides accuracy based on MR image quality, features, contrast, brightness etc. These methods show upto 95-97% of accuracy. In the next decades, Deep Learning (DL) architectures such as Deep Belief Network (DBN), Deep Neural Network (DNN), and Convolutional Neural Network (CNN) are introduced used and they are mainly focused on the fields as image recognition, natural processing, video recognition, etc. The CNN model used to recognize the tumour upto 96% of accuracy. To enhance the accuracy in brain tumour detection, a Sequential Recurrent Neural Network (SRNN) model is implemented in which instead of MR images, symptoms are considered to predict brain tumour. These symptoms are obtained through Optimal Two Phase Feature Selection (OTPFS) technique. The proposed SRNN-OTPFS model is compared with machine learning algorithms with morphology and histology fixed as a target feature. The proposed model increases the accuracy of 2 % compared to the machine learning model in both morphological and histological aspects.

Keywords: *Machine Learning, Deep Learning, SRNN, OTPFS, MR images.*

I. INTRODUCTION

According to the 2016 CNS WHO, there are more than 155 types of Brain Tumours (BT) classified [1]. The brain tumour can be divided into two groups. They are benign tumours and malignant tumours. The brain tumour cells are replicated by itself and grow abnormally. The Benign tumour cannot spread but they increase in size. So they increase the pressure of the brain and interfere with mental functions. The benign tumours are called Primary Brain Tumours. Malignant tumours are very aggressive and can grow very fast. It also infiltrates the surroundings of the brain; sometimes it will enter into the brain and spinal cord. The malignant tumours are also called Secondary Brain tumours. Hospital Based Cancer Registry (HBCR) [2] reports 32.5 % of males and 36.5 % of females who are in the age group of 5 to 9 years were affected by brain and nervos system cancers.

Brain tumour is a tenth leading [3, 22] disease in the world. It is an aggressive disease, so the affected cells are replicated as fast as possible. It leads to a decrease in the survival rate of human life. It is very tough and crucial process to detect tumours at the earliest using image processing techniques. Medical imaging is a prominent technique which plays a vital role in disease diagnosis, clinical monitoring and treatment planning. In image analysis, segmentation of image is a difficult task, in medical field clinicians or oncologist use MR scan, Computed Tomography (CT) scan and ultrasound scans. These technologies are very helpful to localize or identify the tumour presence but the prediction of brain types of tumour is a challenging task in medical field. For classification and detection of brain tumours several machine and deep learning algorithms are utilized.

Deep Learning approach is a growing research field in medical image analysis to predict presence or absence of the disease. Different forms of DL architectures [4] in which RNN, CNN are the examples of supervised

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algorithms in DL. Here new model SRNN-OTPFS model is proposed to improve the accuracy of brain tumour detection through symptoms. SRNN is used to process sequential, gene expression data. There are variety of brain tumours occurred in human such as glioma, astrocytoma, meningioma, anaplastic astrocytoma, oligodentroglioma, medulloblastoma, ependymoma etc., it can be classified and treated depends on the location and symptoms. The following common symptoms [5] are encountered in brain tumours affected patients. Severe and persistent headaches in the morning, vision changes, vomiting, seizures, nausea, neck pain, motor movement, behaviour change, neurological sign, memory loss, coordination problem, mental status, speech problems, walking changes.

The pare is organized as, related review of literature in section 2, proposed methodology and block diagram in section 3, dataset in section 4, results and discussion in section 5 and concludes with conclusion and references.

II. LITERATURE REVIEW

Disha Sushant Wankhede and R.Selvarani [6], proposed a architecture Multi Level Layer modelling in CNN (MLL-CNN) to select features based on feature weight on MR images. A dimensionality reduction algorithm Grey Wolf Optimizer combined with rough set theory is used in MLL-CNN and shows 95% of accuracy. Xiaxing Wu [7] et.al, proposed LSTM model to detect brain tumour earlier based on Tumour Marker (TM) test. The TM-LSTM model works efficiently on real clinical data and shows 93%-95% of accuracy.

Abdul Harnan Khan [8] et al., proposed an intelligent model to identify brain tumour using deep learning called Hierarchical Deep Learning based Brain Tumour (HDL2BT) which classify BT into 4 categories such as Glioma, Meningioma, Pituitary and no tumor classes with the help of CNN method. This HDL2BT shows 92.13% of accuracy and help as a clinical assistance in the field of medical diagnosis.

Madona B Sahaai [9] et al. proposed a method for BT image segmentation based on tumour location using Stacked Auto encoder and DNN. This system shows 95.3% of accuracy by fine tuning hyper parameter of DNN as 50 epochs. Aryan Methil [10] proposed a method to detect BT by applying image processing techniques. The pre-processed MR images have attributes such as tumour shapes, size, location and texture given as input to the CNN model for classification and shows 97.94%of accuracy.

Varun Totakure [11] et al., proposed a model to detect BT using CNN based on symptoms. SNN model is used to classify the histological types of BT based on symptoms. For further confirmation CNN is used on MR images and shows 99.89% of accuracy and SNN model gives 99.36% of accuracy in detecting BT. Kokila [12] et al. proposed a model called CNN based multi-task classification model. This model detects whether a patient have BT or not. If BT present, this model classify tumours by its grade (I, II, III, IV or Unknown) and identify tumour type (Glioma, Meningioma, Astrocytoma etc.,) by the location. This model shows 95% of accuracy.

Francisco [13] et al. proposed a multiscale approach to detect BT and segmentation using Deep CNN. The input images are processed in different processing pathways using CNN. This fully automated multi pathway CNN architecture shows 97.3 % of accuracy. Javarla Amln [14] et al., discuss different Machine Learning (ML) algorithms to detect and classify BT using MR images. The histological types of BT depend on structure shape, size and location. The segmentation technique on MR images not enough to detect BT in earlier stages.

Ramin Rajbarzadeh [15] et al., proposed an effective segmentation system to detect sub- structure of MR images. Instead of using whole image, the part of the image in a slice is given as input to the Cascade CNN which segments the images. To improve the accuracy of the segmentation system, a new method Distance-wise- Attention introduced and shows 92.03% of accuracy. Jaeyong [16] Kang et al. proposed a Framework in which features of MR images to classify BT using ML classifiers. In this framework, MR images are pre-processed and fed into the CNN model as input to extract features. The top three deep features are selected based on the result obtained from ML classifiers.

Milica M.Badza and Marko C.Barjaktarovic [17] proposed a new CNN architecture to classify Glioma, Pituitary and Menigioma BT, which takes input as T1 weighted contrast enhanced MR images. The new CNN architecture with 10 fold cross-validation method used as an effective decision support tool in medical diagnosis system and shows 96.56%of accuracy. B. Yin [18] et al. suggested a new classifier on Neural Network using

Multi-Layer Perceptron with Improved Whale Optimization (MLP-IWOA) Algorithm. MLP-IWOA shows better results than traditional ML classifiers such as SVM, RF.

M. W. Nadeem [19] et al. proposed a hybrid framework called Three Pathways CNN (TP-CNN) model for BT segmentation. To calculate accuracy of a model, Dice Similarity Score used and shows 81% of accuracy. Raja [20] et al. proposed a new hybrid approach called Deep Auto Encoder using Bayesian Fuzzy Clustering (DAE-BFC) for BT classification. In this approach non- local mean filter used for noise removal BFC for segmentation. DAE with Java Optimization (DAE-JOA) Algorithm used for classification.This hybrid approach achieves 98.5% of accuracy.

Yangfan Zhou [21] et al. proposed a Gradient Update Algorithm based on Maximum Probability Cross Entropy Loss Function (MPCE) for NN classification. To evaluate the performance of MPCE, CNN architecture is used and shows upto 95.33% of accuracy on training dataset and upto 85.36% of accuracy on testing set.

In proposed work the following issues are focused:

- BT is an aggressive disease, the size of the tumour grows rapidly. The diagnosis of tumour at initial stage using MR images is highly risk task and expensive.
- Due to the border of BT cells in MR images, the segmentation process is very tedious.
- Extracting feature from MR images must be accurate otherwise it leads to inaccurate result.
- Existing system based on binary classification they focus only whether tumour present or not and use pre-defined feature selection (Information Gain, correlation, Gini index etc) algorithms and classifiers (SVM,RF etc.,)

The contribution of this paper is:

- Instead of using MR images, SRNN-OTPFS model use patient's health records to find BT.
- Symptom based dataset (OTPFS) is obtained from EFFS and IFD algorithm. [24, 25].
- Deep learning algorithms extract the features automatically. Features are processed and fed as input to the SRNN model. The model trained based on morphology and histological types of BT.
- The proposed model reduce the redundant information through Back Propagation Error.
- Multi-class classification is focused to improve the accuracy of proposed model. It shows the accuracy of 95.96 % based on morphology as a target feature and 98.01 % of accuracy based on target attribute histology.

III. METHODOLOGY

Deep Learning (DL) is an evolution from Machine Learning (ML) which can work with Artificial Neural Network (ANN) and includes predictive and statistical modelling. DL plays a significant role in handling both structured and unstructured data. DL also referred as DNN and have three layers, the layers are used to improve and optimize the accuracy of a model. Data runs through the set of layers called "Neural Networks" in which simplified representation of data is passed to next and further layers. Input layer (Accept the input features from a known dataset), Hidden layer (to train the input feature) and Output layer (outputs the required or estimated feature). The general representation of DL layers are shown in Fig 1.

3.1 Sequential Recurrent Neural Network (SRNN):

SRNN is a DL algorithm which process the sequential data and maintains internal memory to handle sequential data in efficient way. SRNN remember previous input and the weights are shared across time. It takes historical information of a dataset for comparison. Loss function in SRNN at time t can be represented by equation (1)

$$Loss(\check{y}, y) = -\sum_{t=1}^{T}(\check{y}\langle t\rangle, y\langle t\rangle) \quad (1)$$

Loss with respect to weight

$$\frac{\partial L(T)}{\partial w} = \sum_{t=1}^{T} \frac{\partial L(T)}{\partial w(t)} \qquad (2)$$

where $(\check{y}\langle t\rangle)$ → predicted output, $(y\langle t\rangle)$ →actual output, T -→total samples, t →time and w →weight.

SRNN use back propagation algorithm for training and applied in every timestamp which helps to found the error between actual and predicted output and can be represented in the following equations (3),(4) and (5).

$$w = w + \Delta w \qquad (3)$$

$$\Delta w = n\,\frac{de}{dw} \qquad (4)$$

$$e = (actual\ error - predicted\ error)^2 \qquad (5)$$

where w→ weight and e→error

Due to Vanishing Gradient Point (VGP- doesn't remember input over long period of time) problem, in SRNN model Long Short Term Memory (LSTM) layer used as a hidden layer. It remembers input for long period of time. LSTM hidden state helps to pass cell state to the next timestamp. LSTM has 3 gates which are responsible to remember and memory manipulations in Neural Network. Fig 2. represent cell state in LSTM layer.

Forget Gate: It is used to remove the value which is no longer used. $T_f(t)$ is zero then remove if it is one it will kept. This gate is used to identify the unnecessary information. It can be calculated using the equation (6)

$$T_f(t) = \sigma\left(w_f\left[a^{(t-1)}, x^{(t)}\right]\right) + b_f \qquad (6)$$

Update Gate: A new vector which can add into the previous cell state. The cell state updated by equations (7), (8) and (9).

$$T_u(t) = \sigma\left(w_u\left[a^{(t-1)}, x^{(t)}\right]\right) + b_u \qquad (7)$$

$$\bar{c}(t) = tanh\left(w_c\left[a^{(t-1)}, x^{(t)}\right]\right) + b_c \qquad (8)$$

$$c^{(t)} = T_f^{(t)} * c^{(t-1)} + T_u^{(t)} * \bar{c}(t) \qquad (9)$$

where $c^{(t)}$ memory variable or cell state in hidden layer. $tanh$ → Activation function

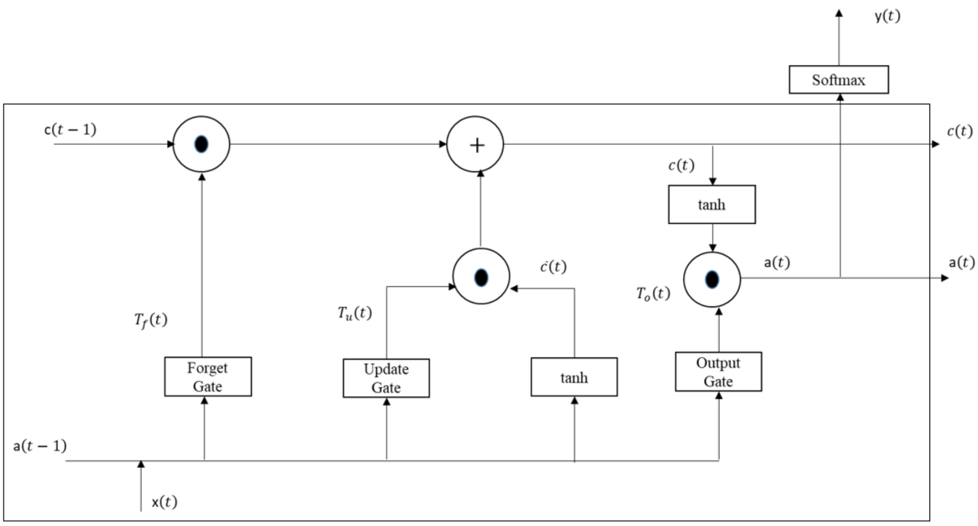


Fig 2. LSTM Cell State

Output Gate: The output of SRNN calculated using Sigmoid Activation function represented in equation (10)

$$T_o(t) = \sigma\left(w_o\left[a^{(t-1)}, x^{(t)}\right]\right) + b_o \quad (10)$$

3.2 Multi – class Classification

To deal nonlinear data Neural Network (NN) concepts are widely used due to large and complex hidden layers. NN acts in major role of Artificial Intelligence (AI) fields such as speech recognition, image classification and sentiment analysis etc. In recent years, multi-class [23] classifier learning plays a vital role in many fields like wireless networks, fuzzy classification systems, and medical engineering etc. ML algorithm such as Support Vector Machine (SVM), K- means algorithm, Naïve Bayes Algorithm and Decision Tree (DT) algorithms are used to provide solution for multi-class classification problems. Compared to traditional ML models, NN model shows higher classification accuracy results.

3.3 Optimal Two Phase Feature Selection (OTPFS) Technique:

The Brain Tumour dataset is downloaded from Kaggle dataset. OTPFS contains two phases. In phase I, features are ranked through multi filters (Information Gain, Chi square, Heatmap and F-score) called Enhanced Filtrate Feature Selection algorithm (EFFS). In EFFS, top ranked features are selected as best features. In phase 2, Iterative Feature Displacement (IFD) is used to achieve high quality dataset called OTPFS dataset.

3.4 Proposed SRNN-OTPFS Model:

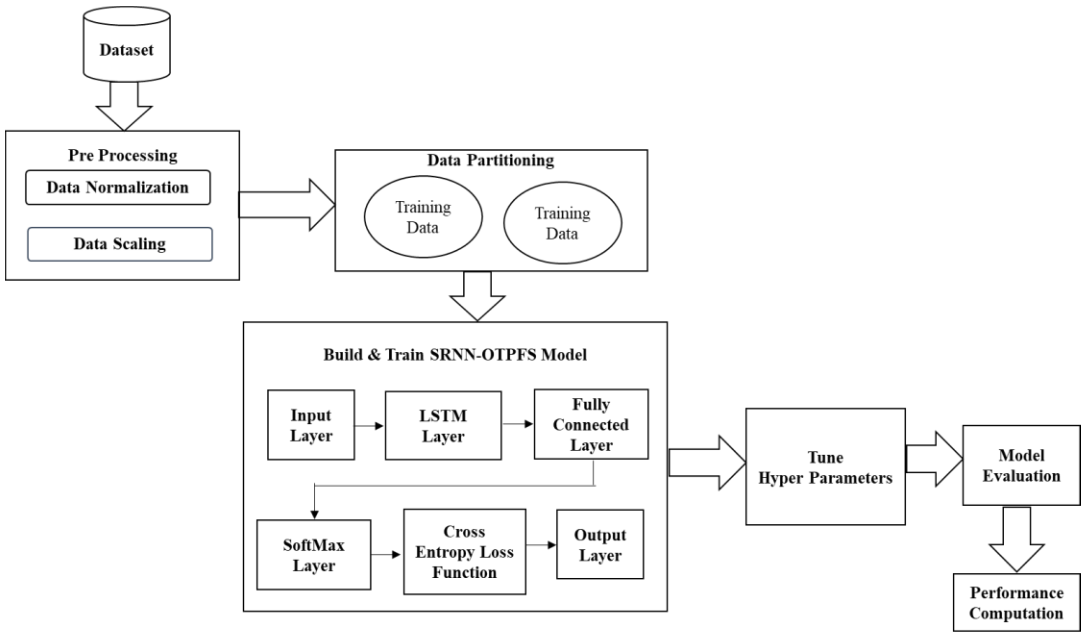


Fig 4. SRNN – OTPFS Model

Dataset: Brain tumour dataset which is obtained through OTPFS technique used as input to the SRNN model. It contains 35 features to identify the histological types of brain tumour.

Pre-Processing: It is an essential step to fine tune dataset. The following initial steps are followed in this work.

Normalization: It is the pre-processing technique in which features in a dataset converted into smaller values as columns in a dataset with common seal and without loss of information. It can be computed through Gradient Descent Convergence (GDC) algorithm and represented by the equation (11).

$$G(w) = \frac{1}{n} \sum_{i=1}^{n} l\left((x_i, y_i), w\right) \quad (11)$$

Scaling: Mean normalization is a scaling technique which distribute data in the range of -1 to +1 with mean value as 0. It is represented by the equation (12).

$$X_{new} = {(X - min(X))}/{max(X - min(X))} \quad (12)$$

Standardization: To make all the features centered around mean and standard deviation value of 1, it can be done by the equations (13) and (14).

$$X_{mean} = {X_{Total}}/{N} \quad (13)$$

$$X_{new} = \frac{X - X_{mean}}{\sigma} \quad (14)$$

Data Partitioning: It is the process to divide the whole dataset into two or three sets called Training set, Testing set and Validation set. Training set is a subset to train a model. Test set is to test the data through trained model and separate the set of data after completing the training process. In every epochs, the same train data is given as input to SRNN repeatedly and to learn a hidden features in the dataset.

In the proposed SRNN-OTPFS model Random Sampling (RS) method is used to partition the data in which data samples are placed randomly and placed in sets based on the specified splitting ratio. Here 80-20 (train, test) splitting criteria is used.

The Validation set used to evaluate the model on every epochs when data is trained on the training set simultaneously. Data portioning is done through equation (15).

$$Train, Test = train\_test\_split(Dataset(X, X_{new}), test\_size) \quad (15)$$

Hyper Parameters: It includes no of neurons, activation function, optimizer, learning rate, batch size, number of layers and epochs. Neurons are specified in the range from 10 to 100.

An activation function used to compute input values of a layer into output values that will be passed to next layers as input. Here ReLu (Rectified Linear Activation Function) and Softmax function used in hidden layers. ReLu function is represented in equation (16).

$$f(x) = max(0, X) \quad (16)$$

Softmax Function is represented as in equation (17)

$$\sigma\left(\underset{z}{\rightarrow}\right)_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \quad (17)$$

where σ → Softmax function, $\underset{z}{\rightarrow}$ → input vector, e^{z_i} → Standard exponential function for input, k→ Number of classes and e^{z_j} → Standard exponential function for output.

Optimizer is helps to reach min loss function. It is also responsible for learning rate and weight change of SRNN. Here Adam optimizer is used and can be represented in equation (18).

$$w_{t+1} = w_t - \alpha m_t \quad (18)$$

where m_t → Aggregate of Gradient at t, m_{t-1} → Aggregate of Gradient at $t-1$, w_t →weight at t, w_{t+1} → weight at $t+1$, α→ learning rate, δL→ derivative loss function, δw_t→derivative weight and β→ moving average parameter.

Loss function: Here MSLE (Mean Squared Logarithmic Error) loss function used to evaluate the model and sows the relative differences of logarithmic transformed values of predicted and actual values in N number of samples. It can be represented by the equation (19).

$$Loss(\breve{y}_i, y_i) = \frac{1}{N} \sum_{i=1}^{N} \left(log(y_i + 1) - log(\breve{y}_i + 1)\right)^2 \quad (19)$$

Learning rate, which controls the size of the step for a model which exhibits minimum loss function. Here learning rate is set as 0.01. Typically lower learning rates are used to achieve minimum loss function. Batch size specifies the number of sub samples in train data for the input data. Smaller batch size makes learning process faster and give high accuracy. In our proposed model, batch size set as 64. Epochs specifies how many number of time the whole dataset is passed to the SRNN- OTPFS model.

IV. DATA ANALYSIS

The dataset contains 35 features which are downloaded from Kaggle dataset. The most important features which are selected through optimal two phase feature selection algorithm used as input to the proposed SRNN-OTPFS model. Among the features morphology and histology chosen as a target variable. The dataset details in given in table 1. The Google Colab is set as running environment. The performance of SRNN-OTPFS model was evaluated using Keras- tensorflow library. Keras is an open source and have high level Application Programming Interface (API) which runs on top of the tensorflow libraries for Neural Network implementation in deep and machine learning concepts. Keras simplify the complex neural network design.

Table 1: Dataset Details

Dataset Name	No of Features	Sample Feature Names	Data Source Link
Brain Tumour	35	Gender, Age, Ethnicity, Race, Location Origin, Morphology, Histology, Recurrences, Prior_Treat, Theraphy, Treat_Type, Tumor_Type, Seizure, Vomiting, Headache, Head_Growth, Motor_Move, Hearing_Impair, Mental_Status, Memory_Loss, Hyper_Tension, Visual_Status, Behaviour_Change, Sensory_Change, Diabetes, Asthma_History, Family_Cancer_History, Fam_Bt_History etc.,	https://www.kaggle.com/datasets/ushavela/brain-tumour

V. RESULTS AND DISCUSSION

Performance Measure: Accuracy

Accuracy is the best performance measure to represent the number of hits based on overall values. Different learning algorithms are used to analyze the accuracy of proposed method.. Accuracy can be calculated by equation (20).

$$Accuracy = \frac{TP + TN}{TP + TN + Fp + FN} \tag{20}$$

Where TP is correctly classified positive, TN is correctly classified negative samples , FP is incorrectly classified positive and FN is incorrectly negative samples. The accuracy of existing methods and proposed SRNN-OTPFS method shown in Table 2. The model is evaluated using morphological feature and shows accuracy of 93.32 % in Random Forest, 95.47 % in Decision Tree, 91.79 % in Support Vector Machine and 87.18 % in Linear Regression classifiers. Compared to the above classifier the proposed SRNN-OTPFS model gives better accuracy of 95.96 %.

Table 2: Performance Measure: Accuracy

Evaluation Method/ Metrics	Existing Learning Methods					Proposed SRNN – OTPFS Method
	Random Forest	Decision Tree	Support Vector Machine	Linear Regression	ANN	
Morphology based Evaluation	93.32	95.47	91.79	87.18	94.6	**95.96**

Histology based Evaluation	95.32	96.05	92.29	93.54	96.64	**98.01**

This SRNN-OTPFS model is also evaluated using histological feature and shows accuracy of 95.32 % in Random Forest, 96.05 % in Decision Tree, 92.29 % in Support Vector Machine and 96.64 % in Linear Regression classifiers. Compared to existing learning method the proposed model shows 98.01 % of accuracy. The proposed model shows Histological based evaluation is better than Morphological based evaluation and also help to increase patients survival rate. The result is shown in Fig 5 (a), (b) and (c).

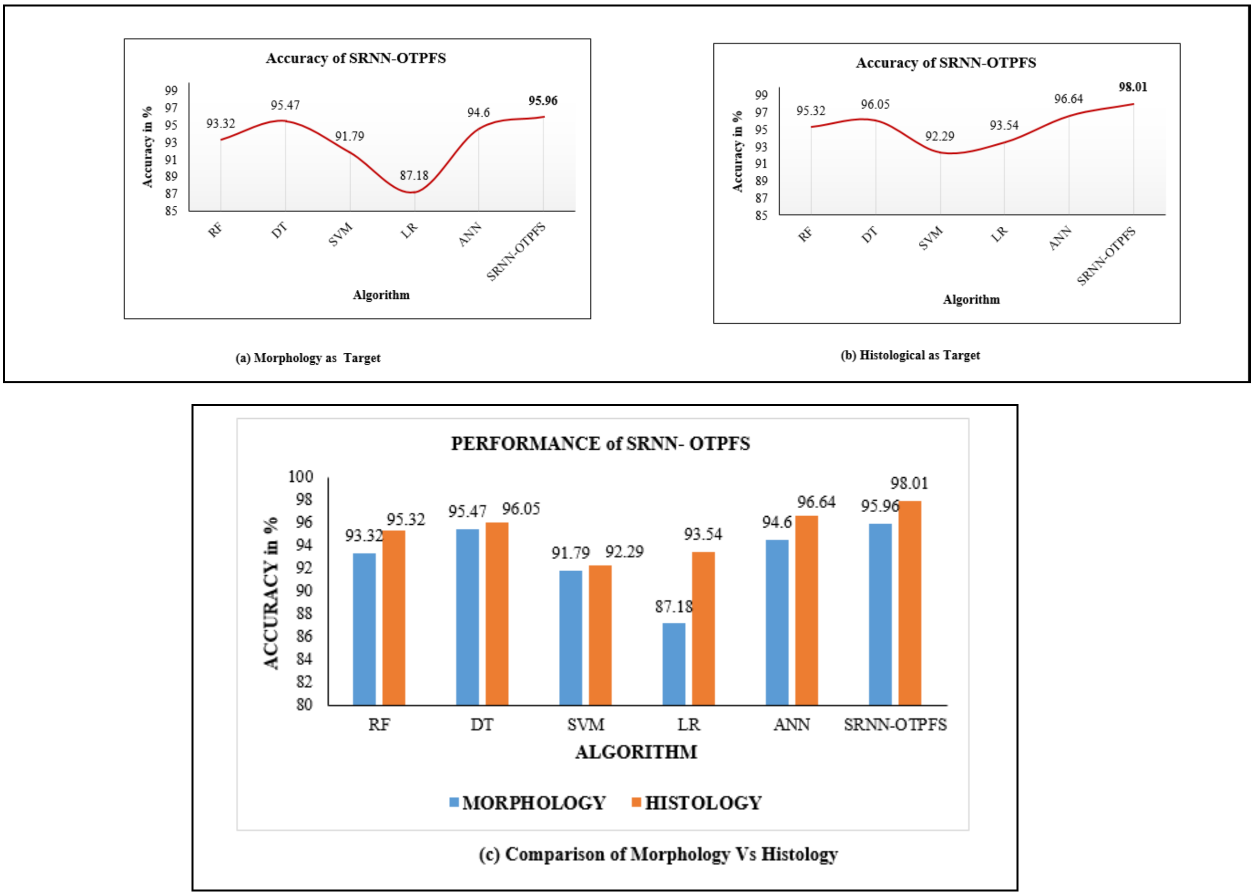


Fig 5 Accuracy of SRNN-OTPFS model based on (a) Morphology (b) Histology (c) Comparison: Morphology Vs Histology

Performance Measure: Error Metrics

In multi class classification error metric is used as one of the performance measure. In the case of continuous or multi class target variable the model is evaluated using error metrics. Root Mean Square Error (RMSE) is one of the evaluator and is easy to compute. It can be calculated using the equation (21).

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(Predicted_i - Actual_i)^2}{N}} \quad (21)$$

Where N is the number of datum in dataset.

Mean Squared Error (MSE) find the average of the squared difference between target value and the actual value predicted by the model. It can be calculated using the equation (22).

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (Predicted_i - Actual_i)^2 \quad (22)$$

Mean Absolute Error (MAE) used to measure the average difference between predicted and actual values based on target variable. MAE is a linear score where all the individual differences are equally weighted in average calculation. It can be calculated by the equation (23).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Predicted_i \; - Actual_i| \tag{23}$$

The result obtained through ANN model and SRNN-OTPFS model showed in Table 3.

Evaluation Method/ Metrics	RMSE		MSE		MAE	
	ANN-OTPFS	SRNN-OTPFS	ANN-OTPFS	SRNN-OTPFS	ANN-OTPFS	SRNN-OTPFS
Morphology based Evaluation	0.1861	4.7363	0.5882	2.550	0.3974	4.7300
Histology based Evaluation	0.2770	6.5858	0.2466	5.4232	0.2372	6.4745

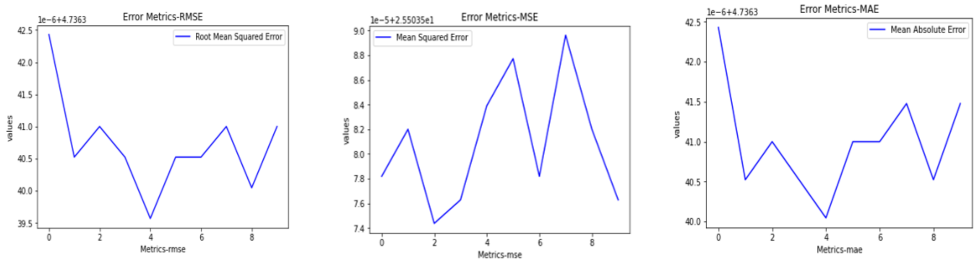
The Error Performance metrics shown in below figures Fig 6, 7, 8 and 9. ANN model shows lower values than SRNN-OTPFS model based on both histological and morphological feature. This error metrics in SRNN-OTPFS model is acceptable because they use more hidden layers than ANN model.

Performance Metrics

(a) RMSE **(b) MSE** **(c) MAE**

ANN-OTPFS_Morphology

Fig 6: Error Metrics: ANN based on Morphology

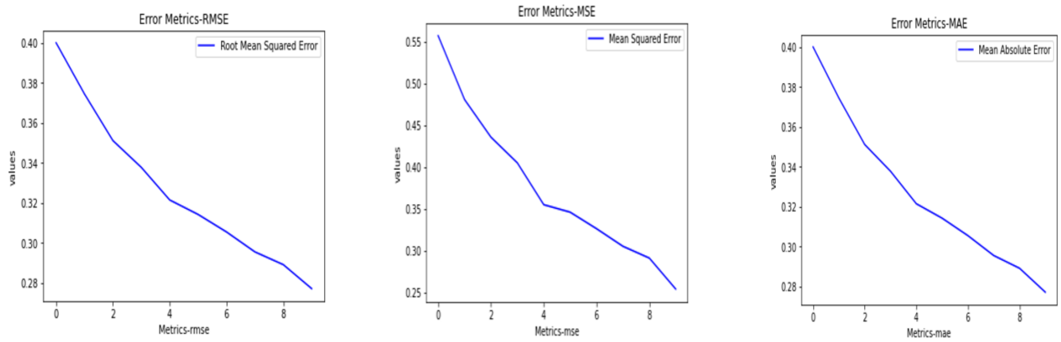


(a) RMSE **(b) MSE** **(c) MAE**

SRNN-OTPFS_Morphology

Fig 7: Error Metrics: SRNN-OTPFS based on Morphology

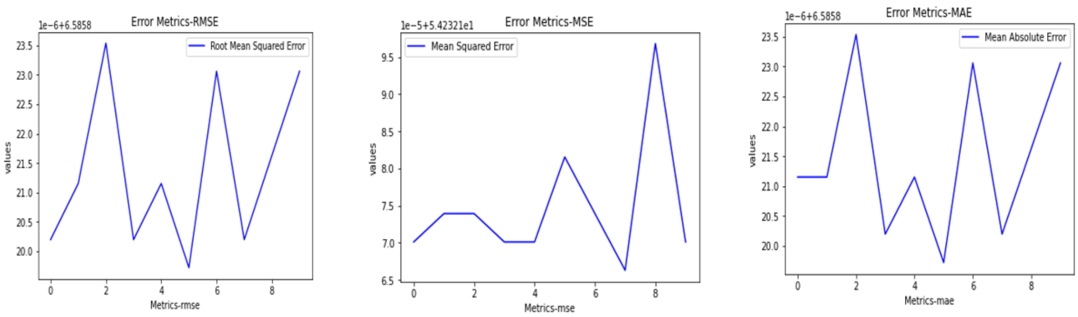
Performance Metrics



(a) RMSE **(b) MSE** **(c) MAE**

ANN-OTPFS_Histology

Fig 8: Error Metrics: ANN based on Histology



(a) RMSE **(b) MSE** **(c) MAE**

SRNN-OTPFS_Histology

Fig 9: Error Metrics: SRNN-OTPFS based on Histology

VI. CONCLUSION

The result of SRNN- OTPFS model compared with existing models. In the dataset both morphology and histology considered as a target feature. In existing model DT algorithm performs well in both target features and shows 95.47% of accuracy in morphological classification and 96.05% in histological classification. In proposed model, compared to morphology based SRNN-OTPFS model histology based model shows higher performance. The accuracy of proposed model shows 95.96% in morphology based and 98.01% in histology based model. The proposed model shows better performance than existing model. The histological features are used to narrow down the treatment option which helps to increase the brain tumour patient's survival rate. The conclusion of this work shows histological feature is better than morphological one in disease diagnosis system. In future, framework has been developed based on OTPFS features which include symptoms to predict brain tumour in earlier stage. Once the histological types are identified it is easy to provide treatment and suggestions for further actions. This framework help as a treatment guideline for clinicians and other medical fields.

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