IDENTIFICATION OF BRAIN TUMOR ON MR IMAGES USING ENSEMBLE LEARNING MODELS

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Abstract

Brain tumor have become a serious health concern for human beings worldwide. It's began with an abnormal growth in the brain size. According to the recent statistics brain tumor caused 246,253 deaths globally. In 2019, the Pakistan Brain Tumor Epidemiology Study (PBTES) has reported 2,750 cases of brain tumor. Manual identification of brain tumors in MRI scans is difficult, time consuming, and subject to variable diagnosis. That's why automated computer-aided systems are important in ensuring accurate and early detection. In the last few years, deep learning classifiers have been used for brain tumor detection, but the individual classifiers are not always consistent. To overcome this, we propose an ensemble as a hybrid approach. This approach based on five classifiers namely CNN, RF, SVM, KNN and LR. All models of machine learning are based on hybrid feature extraction to achieve better output and we use soft voting technique to combine the output of all classifiers for more reliable decisions. In this study we use a dataset of 4600 MRI images for validation. We also include another unseen dataset. On the validation data, the top accuracy for the ensemble is 97.5%. Experimental results on the unseen data (600 MRI images) directly show that the ensemble method is better than each individual model. The individual accuracies were: CNN 91.67%, RF 90.67%, SVM 90.83%, KNN 89.67% and LR 88.83%. The ensemble accuracy jumps to 97.17 % confirming the workability of the hybrid approach. This study shows that ensemble learning can dramatically enhance the performance of brain tumor detection, so it is a promising method that could be used in clinical decision support system.

INTRODUCTION

Brain tumors continue to pose a massive global health problem and they are starting to be felt in Pakistan due to the recent research. With most of the diagnoses coming out of the public hospitals. Similar to a study conducted in Rawalpindi between 2015 and 2019 which revealed the prevalence of ependymomas, pilocytic astrocytoma, diffuse gliomas and medulloblastoma in children, pediatric research also suggests that these tumor types are most common in children.[1,2] The process of manually identifying brain tumors in MRI scan is not an easy task to accomplish, it is time consuming and inconsistent among specialists. This is why the application of automatic computer aid diagnosis systems became relevant in order to be able to detect faster and more reliably. This is the aspiration of the deep learning models, but since there is the privilege of using a single classifier, there might be poor or inaccurate prediction. In order to resolve this our research study a hybrid ensemble method is looked into where an existence of five classifiers i.e. CNN, random forest, SVM, K- nearest neighbors and logistic regression exist. The four machine learning models were trained with hybrid feature extraction and we fused the results of the models with the use of soft-voting to have more stable results.

Brain Tumor MRI Images Identification and Classification Based on the Recurrent Convolutional Neural Network as proposed by Vankdothu and Hameed (2023). [3] proposed an automated brain tumor detection system using Recurrent Convolutional Neural Networks (RCNNs). The K-Means Clustering (IKMC) algorithm is used to conduct the segmentation and the Gray Level Co-occurrence Matrix (GLCM) is used to extract texture-based features that include contrast, energy, homogeneity, and correlation as salient features. The model based on RCNN had an accuracy of 95.17 which is higher than the traditional classifiers.

Ensemble Combination of CNN for MRI-Based Brain Tumor Classification proposed by Sidqi, Santos and Harini, [4] Designated CNN1, CNN2, and CNN3 variants of the convolutional neural network are combined with the majority and weighted averaging methodology. CNN1 (0.90-0.91) and CNN3 and CNN2 (0.82-0.87) demonstrate the better individual performance of CNN3. As the architectures are conglomerated through the suggested ensemble plans, the additional gains in performance are realized, CNN3 reaches the accuracy of 0.96, CNN1 and CNN2 reach 0.94-0.95 and 0.91-0.92 respectively. These results highlight the point that the ensemble configurations have the ability to combine complementary strengths of the underlying models.

A Deep Analysis of Brain Tumor Detection with MR Image using Deep Learning Networks by Mahmud, Mamun, and Abdelgawad (2023). [5] The proposals CNN results were compared with the ResNet -50, VGG16, and Inception V3 in terms of the conventional metrics like the accuracy, the recall, the loss, and the area under the curve (AUC). Training and testing were performed on a set of MRI consisting of 3, 264 images. The CNN model has topped the accuracy of the tested models with a value of 93.3, AUC of 98.43, recalls of 91.19 and a loss factor of 0.25, thus concluding that the proposed CNN architecture is a powerful tool to identify various types of brain tumors at their initial stages and it demonstrates that the architecture can outperform popular pre-trained networks in case of an appropriate design.

Classifying Brain Tumors on Magnetic Resonance Imaging by Using Convolutional Neural Networks proposed by Gomez-Guzman et al. [6] they used the process of thorough preprocessing, followed by training of seven different CNN models: a baseline Generic CNN, ResNet50, InceptionV3, InceptionResNetV2, Xception, MobileNetV3 and EfficientNetB0. The architectures were tested with accuracy measures to establish them as appropriate in this task of classification.

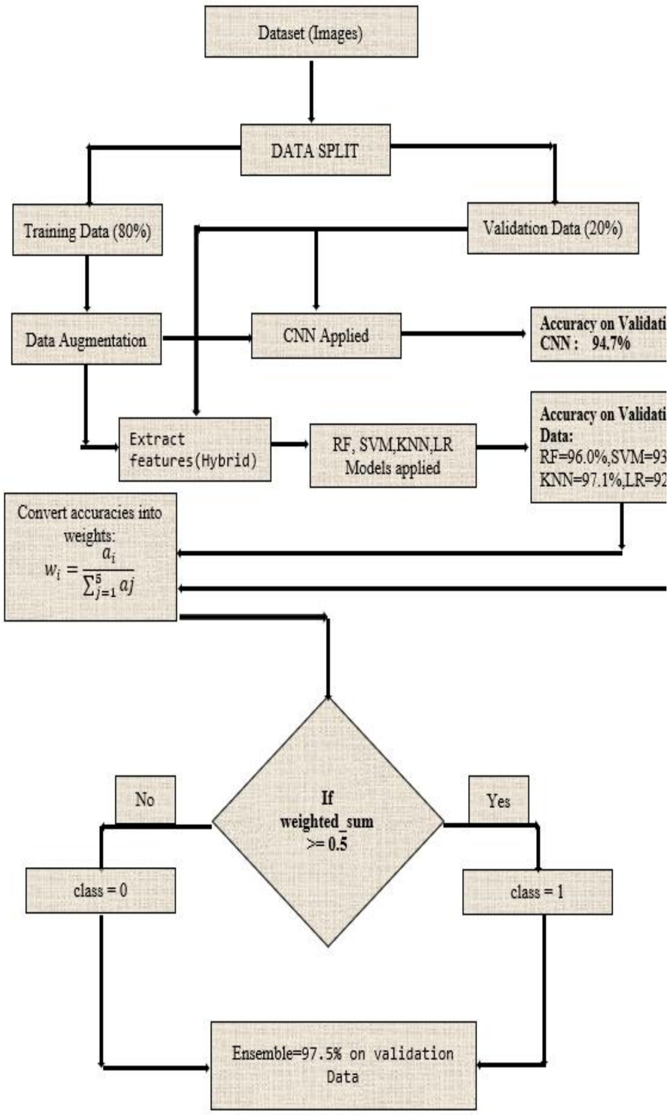
Among the models discussed, InceptionV3 proved the most effective, with an average accuracy of 97.12 percent and therefore being better than the models.

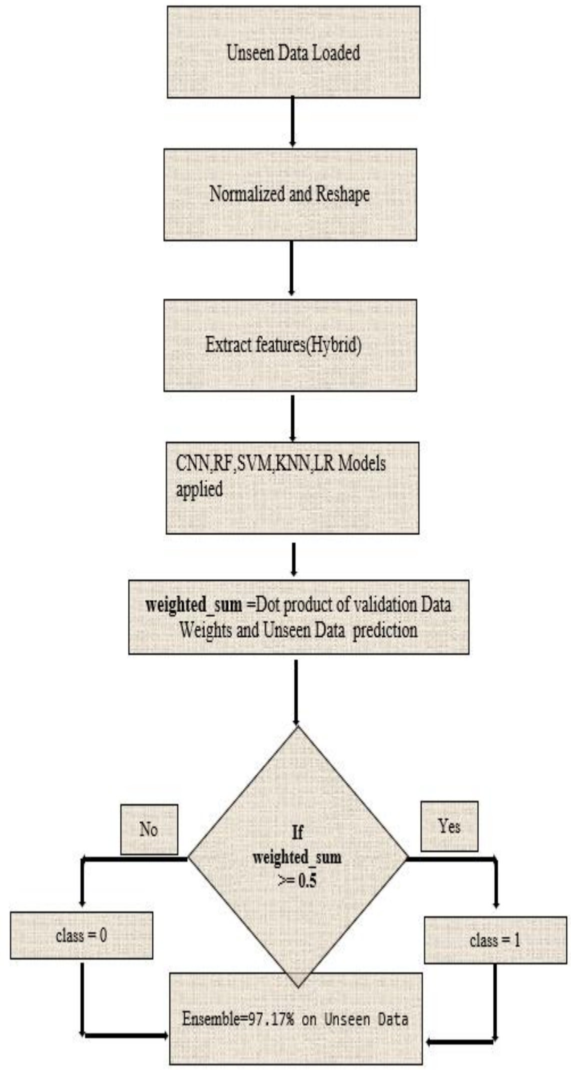
MRI-Based Effective Ensemble Frameworks for Predicting Human Brain Tumor proposed by Khan et al. (2023), [7] the suggested methodology derives deep convolutional features with the convolutional neural networks (CNNs) to comprehensively describe MRI images. Original models that were to be analyzed included five models: the Random Forest (RF), K-Nearest Neighbor (K-NN), the Decision Tree (DT), the Extreme Gradient Boost (XG-Boost) and the AdaBoost. The three top-performing models of XG-Boost, AdaBoost and RF were then combined to create an ensemble voting classifier (XG-Ada-RF) that made final binary predictions (tumor vs. non-tumor). The results of experiments have shown that the ensemble method is better than each of the individual models with a 95.9% accuracy in detecting tumors and 94.9% in the normal classification. Brain Tumor Segmentation Using U-Net Enhanced with Attention proposed by Li (2023). [8] suggested an improved U-Net framework, the so-called ArUnet, to brain tumor segmentation in the MRI images.The quality of results on the BraTS2021 dataset provided in the experiment indicates that ArUnet achieved 95.54% accuracy, as compared to traditional U-Net models. This result shows that the combination of the attention mechanisms and residual connections significantly improves the ability of the model to extract features of abstractions and map tumor locations effectively.

MRI-Based Brain Tumor Detection Using Convolutional Deep Learning Methods and Chosen Machine Learning Techniques proposed by Saeedi et al (2023). [9] The 2D CNN architecture was used with eight convolutional layers. It was empirically found that the 2D CNN achieved a training accuracy of 96.47, mean recall of 95 and an area under the curve of 0.99 to 1. The auto-encoder was slightly underscoring with an accuracy of 95.63%. The K -Nearest Neighbor outperformed the Multilayer Perceptron (86 -percent vs. 28 -percent) among the traditional classifier models. Significant superiority of the CNN approaches compared to the traditional ones was statistically proven (p 0.05). The authors therefore inferred that the 2D CNN provides best results in terms of performance and computation cost making it a possible candidate to be incorporated into clinical radiological processes to supplement diagnostic accuracy in brain tumor detection.

1. Material and Methods

This methodological pathway takes place through a series of specially controlled steps: one obtains a representative dataset, pre-processes it rigorously, judiciously adds to the data, normalises the models, extracts the hybrid features, performs dimensionality reduction, trains a classifier, an ensemble of weighted soft-voting, and carefully evaluates the data on unseen data. Every of the constituent phases has been chosen purposefully so as to enhance the strength and accuracy of the whole classification system.





1.2. Preprocessing

Preprocessing is necessary for making the intensity differences and standardizing the input size. All of the images were sized to 200x200 pixels. Pixel intensities were normalized within a range of 0 - 1:

X train = x train / 255.0

X test = x test / 255.0

This normalization helps to do stable training of neural networks and to have better convergence.

1.3. Data Augmentation

In order to improve generalization and mitigate overfitting, model specific deterministic augmentation techniques have been used. Each classifier made an individual choice in the augmentation strategy with an emphasis on the features that are most relevant for the classifier to perform well.

1.4. Extraction Features (hybrid) [Embedded CNN + HOG + Wavelet]

Although convolutional neural networks learn hierarchical representations of images autonomously[10,11], conventional classifiers of the machine-learning paradigm, like Random Forests, Support Vector Machines, k-Nearest Neighbors and Logistic Regression, use manually designed feature vectors[12,13]. To take advantage of both the complementary nature of deep-learning representations and of engineered descriptors, a hybrid approach in feature extraction was taken.

The hybrid feature vector is a combination of three different classes of features:

1. **CNN features** - high level representations (abstract features) that are learned from the images [14,15].
2. **Wavelet features** - Extracting multis impregnated texture information using wavelet [37].
3. **HOG** - finding the shapes and edges designs [37, 40].

This integration helps to improve the discriminative power of the downstream machine learning classifiers to improve Ensemble classification accuracy.

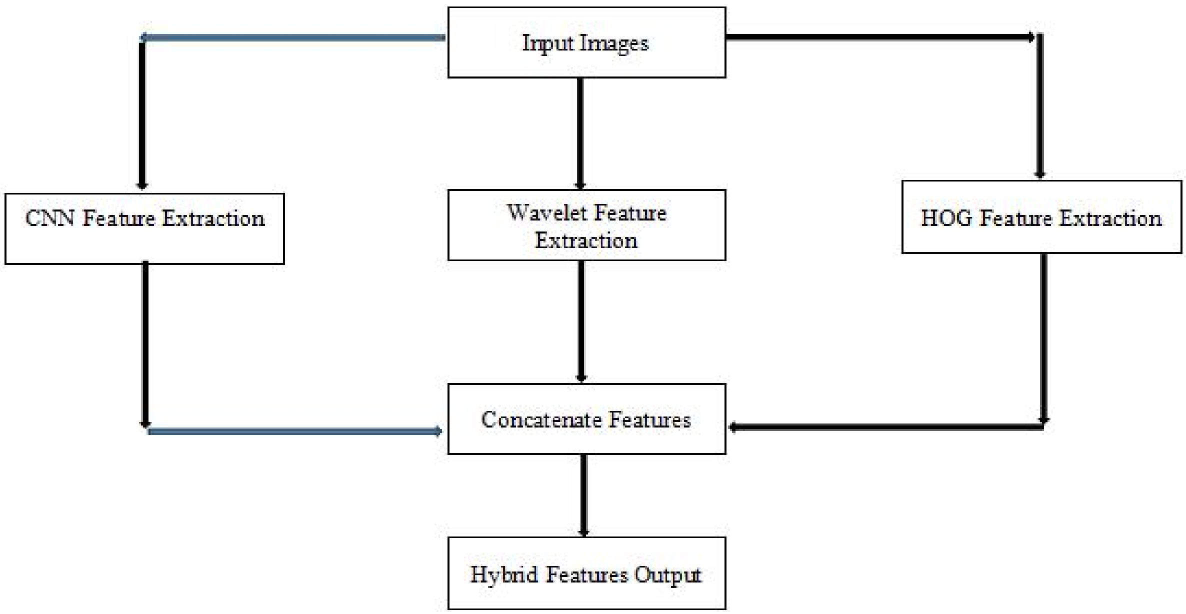


Fig 2.2. Hybrid Feature Extraction Flowchart

2.5. Classifiers without put accuracy on validation data

Mathematical Representation: Convolution Operation:

For a given input image, I and filter K:

$$S(i,j) = (I * K)(i,j) = \Sigma_m \Sigma_n I(i+m, j+n) \cdot K(m,n)$$

Where * denotes convolution, S is the resulting feature map.

Activation Function (ReLU):

$$f(x)=\max(0,x)$$

This introduces non-linearity, allowing the network to learn complex patterns.

Pooling Layer:

$$P_{i,j} = \max(S_{i:i+1, j:j+1})$$

Max-pooling reduces spatial dimensions while preserving dominant features.

Fully Connected Layer:

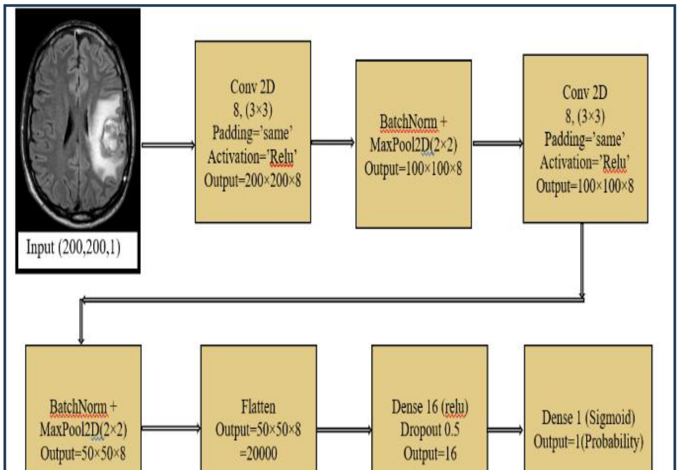
$$y=\sigma(Wx+b)$$

Where σ is the sigmoid function for binary classification.

Table 2.1: ***CNN parameters used in model trainings***

Layer Type	**Parameters / Details**	**Purpose**
Conv2D	8 filters, 3×3 kernel, ReLU,	Learn local features (edges, patterns)

Layer Type	Parameters / Details	Purpose
	padding='same'	
BatchNormalization	Default parameters	Stabilize learning and accelerate convergence
MaxPooling2D	Pool size 2×2	Reduce spatial dimensions, extract dominant features
Conv2D	8 filters, 3×3 kernel, ReLU, padding='same'	Capture more complex features
BatchNormalization	Default parameters	Maintain stability during training
MaxPooling2D	Pool size 2×2	Further downsample spatial features
Flatten	—	Convert 2D feature maps into 1D vector
Dense	16 units, ReLU activation	High-level abstract representation
Dropout	0.5	Regularization to reduce overfitting
Dense (Output)	1 unit, Sigmoid activation	Binary classification (tumor vs. healthy)



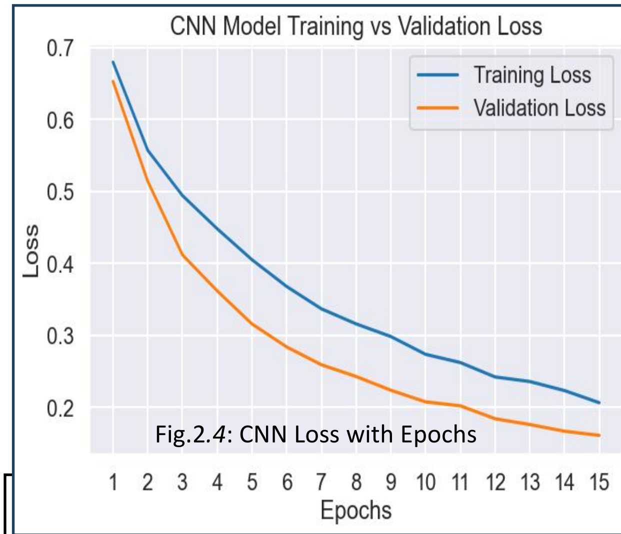
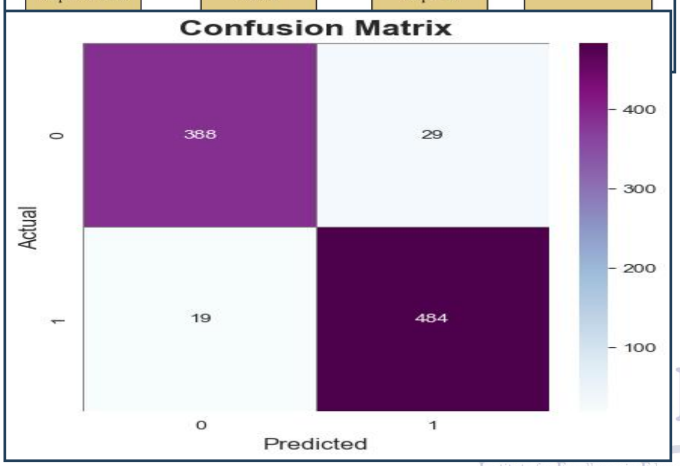
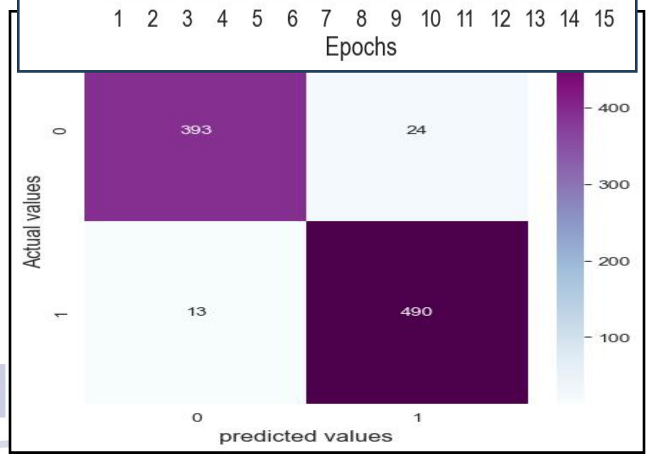


Fig.2.4: CNN Loss with Epochs





4.5.2.Random Forest Training

RF model is trained on the hybrid features of PCA reduced and scaled.[16,17]:

rf = RandomForestClassifier(n estimates=7, random state=42)

rf.fit(X_train_scaled_rf, y_train_rf)

Evaluation

- Training Accuracy: 99.81%
- Test Accuracy: 95.97%

Fig.1.3:Diagram of CNN architecture with layers,

2.2.1. Support Vector Machine (SVM)

SVM is the supervised learning algorithm which defines the best hyperplane between two classes.[10,17,18]

Training

svm = SVC (C=1e -3, kernel = linear,

class weight = balanced, probability= True, random state=42)

Evaluation

- Training Accuracy: 92.47%
- Test Accuracy: 93.15%

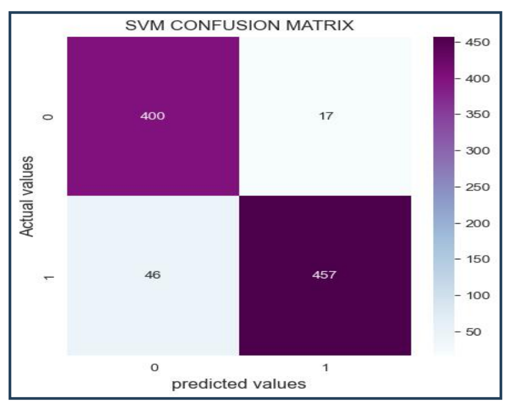


Fig.2.7 SVM Confusion Matrix on

2.2.2. K-Nearest Neighbors (KNN)

Training

knn = KNeighborsClassifier(nneighbors=3, weights= distance, metric=manhattan).

Evaluation

- Training Accuracy: 99%
- Test Accuracy: 97.07%

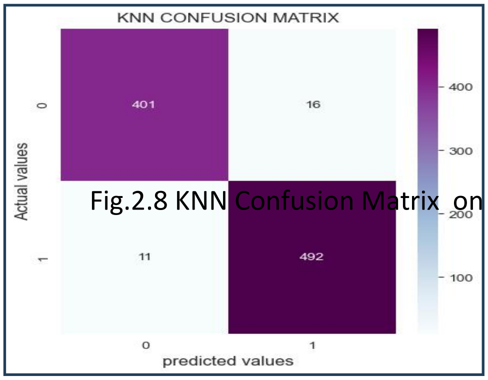


Fig.2.8 KNN Confusion Matrix on

2.2.3. Logistic Regression (LR)

Training

LogR = LogisticRegression(C=0.001, solver= liblinear, penalty=l2,maxiter=2000, class_weight='balanced', random_state=42)

Evaluation

- Training Accuracy: 97.98%
- Test Accuracy: 92.07%

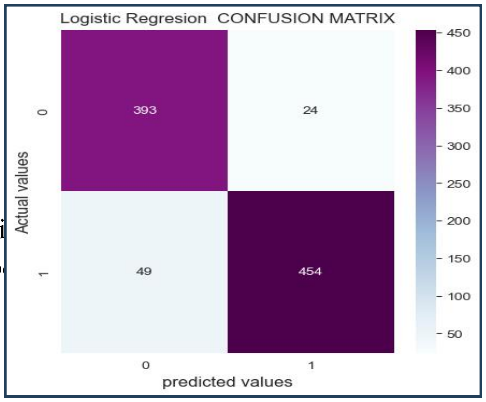


Fig.2.9 LR Confusion Matrix on Validation Data

2.2.4 Weighted Soft Voting Ensemble

In **soft voting**, classifiers don't give a direct label (like 0 or 1), but i each class. These probabilities are combined, **weighted by the p** make the final prediction:

$$\text{ensemble} = \begin{cases} 1 & \text{if } \sum_{i=1}^{M} w_i p_i \geq 0.5 \\ 0 & \text{otherwise} \end{cases}$$

Where:

- **M** = Number of classifiers
- p_i = Probability that classifier i predicts class 1
- w_i = Weight of classifiers
- This method gives **more importance to the models that are more reliable** when making the final decision

2. Result and Discussion

the experimental findings of the proposed hybrid ensemble model in the brain tumor Identification. The individual performance of the classifiers, Convolutional Neural Network (CNN), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Logistic Regression (LR) is initially analyzed. Thereafter, the ensemble model that uses these classifiers with soft voting is studied. The findings are in the form of accuracy, precision, recall, and F1-score. A comparison between the individual and collective classifiers shows the effectiveness of the offered approach.

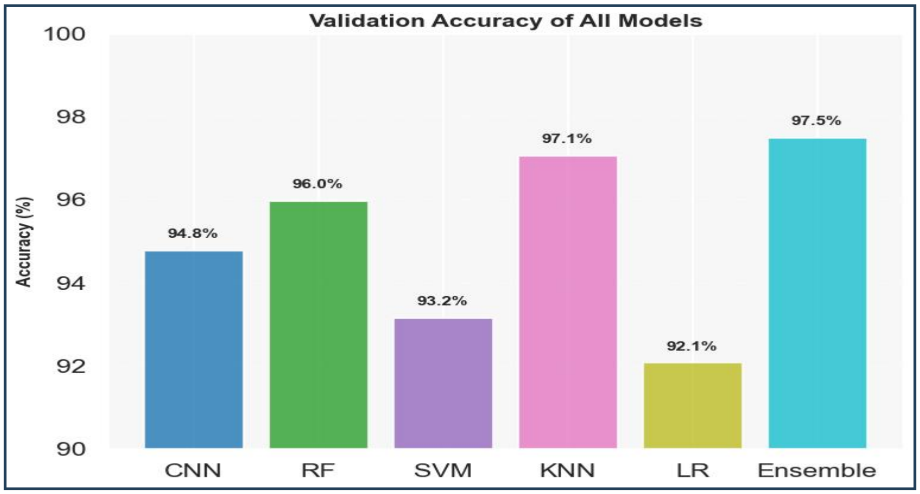


Fig 3.1. Accuracies of Individual and Ensemble Models On Validation Data

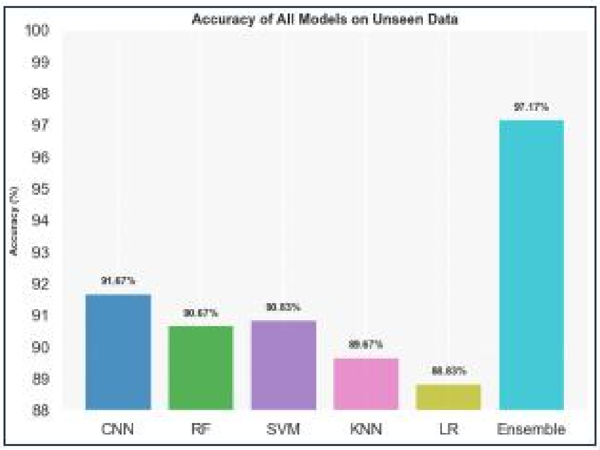


Fig 3.1. Accuracies of Individual and Ensemble Models On Unseen Data

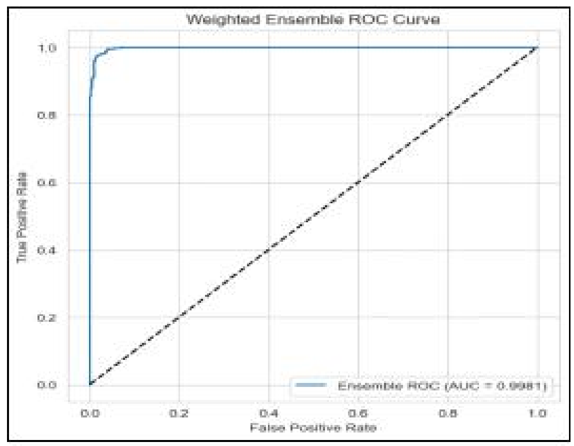


Fig 3-4: Ensemble Model ROC Graph AUC Score on Validation Data

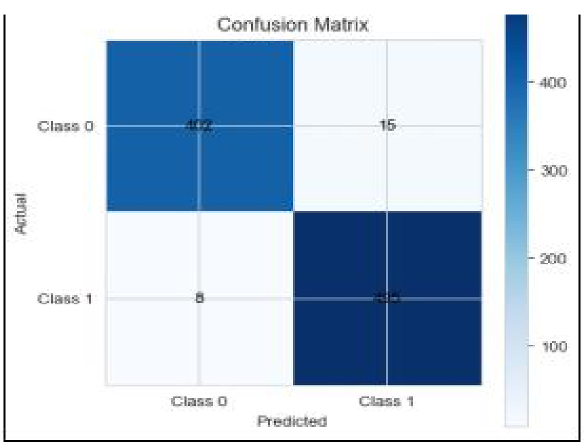


Fig 3-3: Ensemble Models Confusion Matrix on Validations Data

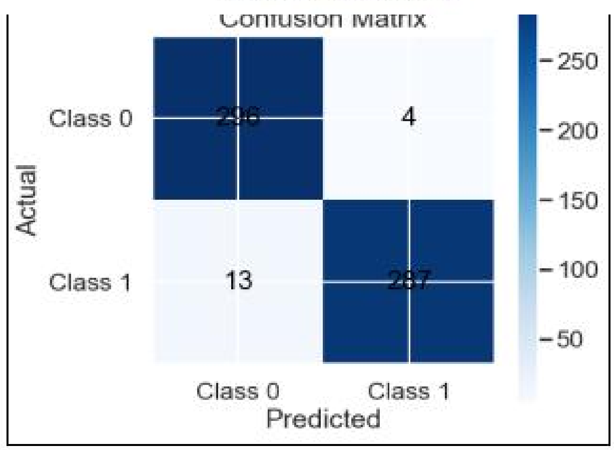


Fig 3-5: Confusion Matrix of Ensemble Models on Unseen Data

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Table 3- 1: Different models with Different Feature Extraction Methods on Validation Data

Method	Classifier	ACC%	Sensitivity %	Specificity %
	RF	94	95	93
	SVM	88.6	88	89
Wavelet	KNN	97.2	96	98
	LR	87.7	86	90
	CNN	94.8	96	93
	Ensemble	97.4	98	97
HOG	RF	93	95	90
	SVM	68.6	94	37
	KNN	97	96	98
	LR	73.5	87	58
	CNN	94.8	96	93
	Ensemble	97.1	99	95
CNN features	RF	80.1	84	76
	SVM	54.7	100	0
	KNN	80.1	76	86
	LR	50.9	16	93
	CNN	94.8	96	93
	Ensemble	91.8	93	91
LBP (Local Binary Patterns)	RF	66.3	80	50
	SVM	54.7	100	0
	KNN	65	80	47
	LR	45.3	0	1
	CNN	94.8	96	93
	Ensemble	87	91	82
GLCM – Gray Level Co-occurrence Matrix)	RF	90.9	91	90
	SVM	67.5	77	56
	KNN	91.2	91	91
	LR	61.4	55	69
	CNN	94.8	96	93
	Ensemble	95.7	98	93
wavelet + CNN features	RF	94.9	95	95
	SVM	88.6	88	89
	KNN	97.2	96	98
	LR	87.6	87	89
	CNN	94.8	96	93
	Ensemble	97.5	98	97
HOG + CNN features	RF	94.9	95	90
	SVM	68.8	94	38
	KNN	97.1	97	97
	LR	74	87	58
	CNN	94.8	96	93
	Ensemble	96.8	99	95
Hybrid (Embedded CNN Feature +HOG	RF	96	97	94
	SVM	93.2	91	96
	KNN	97.1	98	96
	LR	92.1	90	94
	CNN	94.8	96	93
	Ensemble	**97.5**	**98**	**96**

Table 3- 2: Different models with Different Feature Extraction Methods on Unseen Data

Method	Classifier	ACC%	Sen%	Spe%
Wavelet	RF	94.50	92	97
	SVM	77.83	64	92
	KNN	93	87	99
	LR	76	66	87
	CNN	91.67	89	94
	Ensemble	95	91	99
HOG	RF	94.50	92	97
	SVM	66.17	86	47
	KNN	85.17	72	98
	LR	67	83	51
	CNN	91.67	89	94
	Ensemble	94.83	93	97
CNN features	RF	85.17	81	89
	SVM	50	100	0
	KNN	84.50	72	97
	LR	49	10	90
	CNN	91.67	89	94
	Ensemble	94.33	92	96
LBP (Local Binary Patterns)	RF	67.50	97	38
	SVM	50	100	0
	KNN	67.33	97	38
	LR	50	0	100
	CNN	91.67	89	94
	Ensemble	92	95	89
GLCM – Gray Level Co-occurrence Matrix)	RF	88.67	81	96
	SVM	69	96	42
	KNN	88.33	79	97
	LR	56.33	38	74
	CNN	91.67	89	94
	Ensemble	95.50	93	98
wavelet + CNN features	RF	93	88	98
	SVM	77.83	64	92
	KNN	93	87	99
	LR	76	69	84
	CNN	91.67	89	94
	Ensemble	95.17	92	98
HOG + CNN features	RF	91.83	88	96
	SVM	66	85	47
	KNN	85.50	73	96
	LR	67.17	83	61
	CNN	91.67	89	94
	Ensemble	94.83	92	97
Hybrid (Embedded CNN Feature +HOG	RF	90.67	86	95

Recording to ROC Graph the AUC Score of Hybrid (Embedded CNN Feature +HOG +Wavelet) Feature Extraction Method Validation Data and Unseen Data AUC Score is High compare to the other Feature Extraction Methods.so this reason this study is using the Hybrid Method

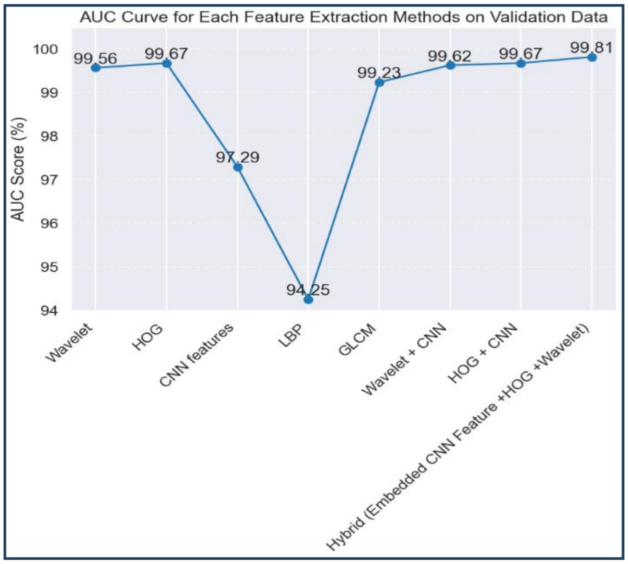

Fig 3- 6: ROC Curve AUC Score on validation Data

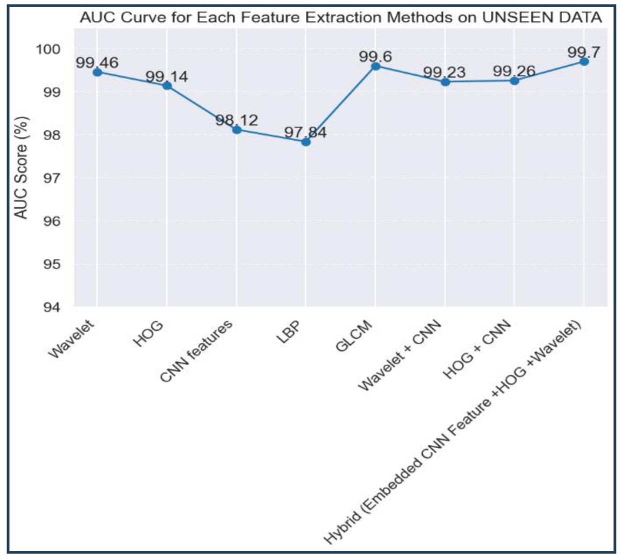

Fig 3- 7: ROC Curve AUC Score on Unseen Data

3.1 Comparison with existing models

Authors	Classification Methods	Feature Extraction Methods	Limitations	Accuracy%
Vankdothu and Hameed	Recurrent Convolutional Neural Networks (RCNNs)	Gray Level Co-occurrence Matrix (GLCM)	GLCM texture features depend on image quality; sensitive to noise.	95.17%
Sidqi, Santos and Harini	Ensemble Combination of CNN	CNN	Training multiple CNNs requires significant GPU resources.	96%
Mahmud, Mamun, Abdelgawad	Deep Learning Networks	CNN	3,264 images may not capture full variability of tumor types. Exact tumor types or subcategories are not detailed	93.3%
Khan et al	Ensemble Frameworks for Prediction	convolutional neural networks (CNNs)	Performance depends heavily on the CNN's feature quality	95.9%
Li et al	Tumor Segmentation Using U-Net	Improved U-Net architecture (ArUNet) Residual	High computational cost due to residual blocks + attention layers.	95.54%

		Network (ResNet) blocks		
Saeedi et al	Convolutional Deep Learning	CNN	Dataset is relatively small (3264 images) for a 4-class brain tumor classification task.	96.47
Our Model	**Ensemble learning Models**	**Hybrid Feature Extraction (Wavelet+HOG +CNN)**	______________	**97.12**

4. Conclusion

4.1. Future Work

1. **Multi-Class Classification**: The system can be extended to include classification of various brain tumor types which include gliomas, meningiomas and pituitary tumors.
2. **Tumor Segmentation**: Introduce the concept of segmentation to detect the accurate locations of tumors, and support the surgical planning and monitoring therapy

4.2. Conclusion

This paper was able to show that a hybrid ensemble model of CNN, RF, SVM, KNN, and LR classifiers can massively enhance detection of brain tumor on MRI pictures. The suggested soft voting ensemble reached 97.5% on the validation Data and 97.17% accuracy on unseen data which is better than the independent models and shows the advantages of deep learning and machine learning methods combination. The used methodology provides a stable and automated resource that could help radiologists, which would possibly minimize the diagnostic errors and enhance patients' outcomes.

The results confirm that:

- Ensemble learning is an important architecture that boosts classification.
- The proposed approach has a wide generalization to training data.

Lightweight deep learning architectures may be used to get high-performance.

In general, this system demonstrates a high potential of helping radiologists to detect brain tumors at an early stage, decrease the workload of the diagnosis, and improve the precision of the clinical decision-making.

This study would form a clear basis to developing the state of the art and clinically applicable brain tumor detection systems through dealing with the current limitations and expanding the framework.

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