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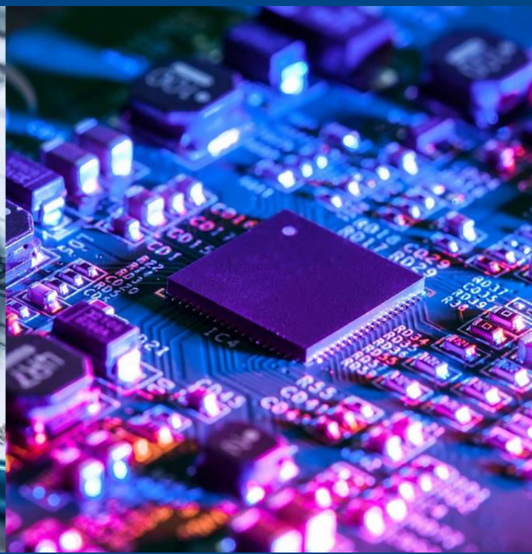

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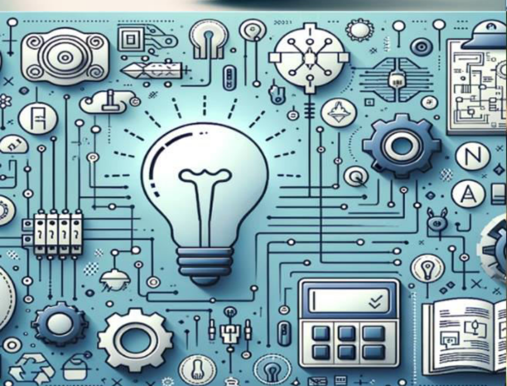

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Brain Tumor Classification using SVM with Gaussian Radial basis Function Kernel

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ABSTRACT: Magnetic Resonance (MR) brain image classification is extremely important in achieving accurate diagnosis and identification of brain tumors. A novel approach for classifying MR brain images is proposed in the present work, where frequency-based feature extraction is performed by Discrete Wavelet Transform, and texture features are captured by Gray Level Co-occurrence Matrix. After extraction, these features are classified using various machine learning algorithms like Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), and Random Forest (RF). The impact of Linear, Polynomial, Quadratic, and Gaussian Radial Basis Function SVM kernels on accuracy is evaluated. Experimental results on the Kaggle Brain Tumor Dataset establish a more accurate and more robust method of brain tumor classification. Comparative results also help in identifying the best-performing model among the algorithms tested.

KEYWORDS: MRI (Magnetic Resonance Imaging), DWT (Discrete Wavelet Transform), GLCM (Gray Level Co-occurrence Matrix), SVM (Support Vector Machine), ANN (Artificial Neural Network), KNN (K-Nearest Neighbor), RF (Random Forest), GRBF (Gaussian Radial Basis Function), Brain Tumor Classification, Feature Extraction.

I. INTRODUCTION

Brain tumor classification from Magnetic Resonance Imaging (MRI) is a critical step in the early and accurate diagnosis of brain diseases. The complex and variable nature of brain tumors make manual interpretation of MRI scans very difficult. Consequently, it can lead to delayed diagnosis or incorrect classification. The use of machine learning for automated classification systems brought forward good results in terms of diagnostic accuracy and robustness.

The project hereby introduces a new comprehensive feature extraction method that makes use of both Discrete Wavelet Transform (DWT) and Gray Level Co-occurrence Matrix (GLCM). First, DWT is used to extract frequency-based features that focus on the structural details of tumors, whereas GLCM captures texture features and will focus on structural details of the tumors whereas GLCM will be in the textural domain to represent contrast, correlation, energy, and homogeneity. These features aim to provide a comprehensive representation of the tumor while improving input quality for classification models.

One of the most vital tasks with the available features is to use Principal Component Analysis (PCA) to eliminate less significant features while maintaining the information which reflects the original ones, and to conduct dimension reduction in order to smoothen out and speed up the computational procedures as well as to improve the classification accuracy. The following machine learning algorithms are applied: Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), and Random Forest (RF). In addition to this, different SVM kernels such as Linear, Polynomial, Quadratic, and Gaussian Radial Basis Function (GRBF) are also evaluated to obtain the best model.

A dataset of Brain Tumor MRI from Kaggle that contains 7023 labeled images in four categories: Glioma, Meningioma, Pituitary, and No Tumor, is used for validation. The dataset is split into 70% for training and 30% for testing. The obtained results show that the GRBF-SVM combined with the DWT-GLCM method is more powerful in classification, with the highest accuracy. Hence, the outcome clearly shows that the detection of brain tumors is possible, and the proposed method could serve as a potential tool in clinical practices.

II. LITERATURE SURVEY

Brain tumor classification using MRI images has been extensively researched to provide a reliable diagnosis and support clinical decision-making. Traditional machine learning approaches that rely on handcrafted feature extraction methods such as Discrete Wavelet Transform (DWT) and Gray Level Co-Occurrence Matrix (GLCM) have proven effective in capturing texture and statistical characteristics from brain MRI scans, which are essential for accurate tumor classification.

Naser et al. (2021) [1] investigated the performance of various Support Vector Machine (SVM) kernels for brain tumor diagnosis using MRI data. Their study emphasized that kernel selection plays a crucial role in improving classification accuracy, reinforcing the effectiveness of SVM when used with robust handcrafted features.

Mehrotra (2020) [2] proposed a novel approach combining DWT for multi-resolution feature extraction with SVM classification. This method successfully integrated spatial and frequency domain information, leading to enhanced tumor classification performance.

Saha and Hossain (2017) [3] employed K-means clustering coupled with Non-Subsampled Contourlet Transform (NSCT) for feature extraction and SVM for classification. Their results demonstrated the significance of advanced texture-based feature extraction in differentiating various brain tumor types.

Deeksha et al. (2020) [4] utilized Artificial Neural Networks (ANN) trained on features extracted by GLCM and other texture descriptors for brain tumor classification. Their findings supported that ANN can effectively classify tumor types when combined with discriminative handcrafted features.

Mishra and Yadav (2020) [5] developed a hybrid model integrating multiple feature extraction techniques, including wavelet and statistical methods, with classifiers such as K-Nearest Neighbors (KNN) and Random Forest (RF). This fusion of features yielded improved accuracy and robustness by capturing the complex heterogeneity of brain tumors.
Abir et al. (2018) [6] applied Probabilistic Neural Networks (PNN) on statistical features derived from MRI images for brain tumor classification. Their approach demonstrated the viability of classical machine learning models combined with well-selected features in achieving reliable classification

Liu et al. (2019) [7] combined SVM with feature extraction methods like GLCM and statistical texture analysis to classify brain tumors from MRI images. Their study highlighted that carefully extracted texture features significantly contribute to the classification task without requiring deep learning models.

Prakash and Mishra (2020) [8] proposed a hybrid machine learning framework leveraging DWT and GLCM features with classifiers such as SVM and RF for brain tumor classification. Their method provided high accuracy by effectively capturing both local and global features of tumors from MRI scans.

Collectively, these studies establish that handcrafted feature extraction techniques such as DWT and GLCM, when coupled with traditional machine learning classifiers like SVM, ANN, KNN, and RF, provide an effective and computationally efficient approach for brain tumor classification. This body of work justifies the methodology employed in the present project, which avoids deep learning architectures and focuses on interpretable features and classifiers.

III. PROPOSED METHODOLOGY

The goal of the modular design of the brain tumor classification system architecture as shown in Figure 1 is to incorporate all important stages from image preprocessing to feature extraction, dimensionality reduction, and classification using classical machine learning models. It emphasizes interpretable handcrafted features such as Discrete Wavelet Transform (DWT) and Gray Level Co-Occurrence Matrix (GLCM), with PCA for feature reduction to preserve relevant information and substantially reduce dimensionality. Reduced feature sets would then be used in training classifiers, including Support Vector Machine (SVM) with kernels (Linear, Polynomial, Quadratic, and Gaussian Radial Basis Function (GRBF)), Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), and

Random Forest (RF). Model performance is evaluated on measures including accuracy, confusion matrix, precision, recall, and F1-score, to gain further insights into classifier capabilities.

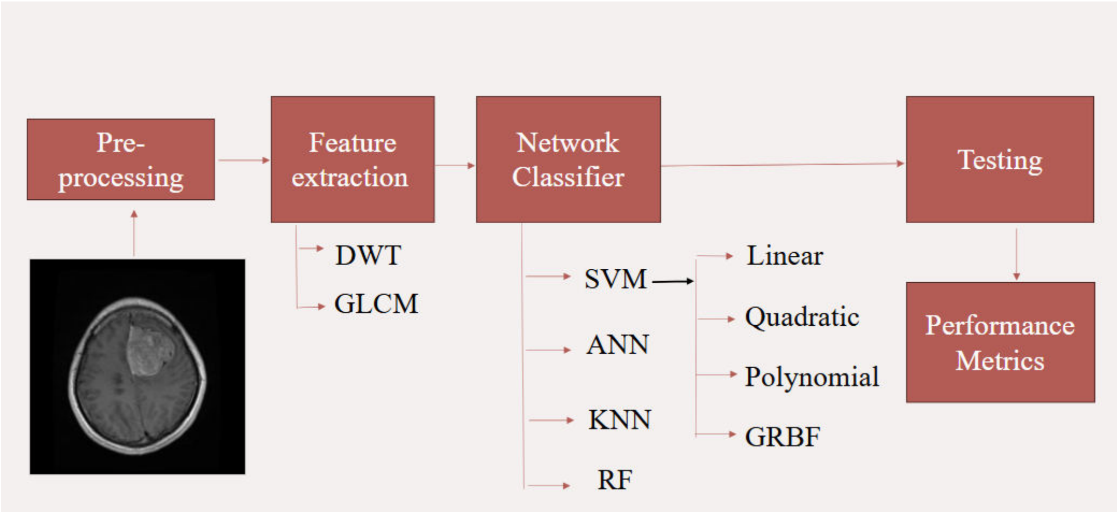

Figure 1: Block diagram for proposed methodology

1. Dataset Loading and Preprocessing

The process starts with loading the MRI brain tumor dataset, resizing and normalizing the MRI images for all samples to ensure uniformity. Preprocessing consists of noise removal and intensity normalization to improve the efficiency of feature extraction. The dataset is divided into training and testing sets, usually with a 70:30 ratio, to validate the model well and prevent overfitting.

2. Feature Extraction

The feature extraction is necessary for differentiating tumor areas from normal brain tissue. There are two primary handcrafted feature extraction methods:

- Discrete Wavelet Transform (DWT): Handcrafted feature-based: Divides MR images into frequency sub-bands to learn information from both frequency and spatial domains to emphasize tumor texture and edges.
- Gray Level Co-Occurrence Matrix (GLCM): The GLCM captures texture features in the textural domain from the MR images and thereby gives statistical measures of the tumor heterogeneity.

These features in turn go on to form detailed descriptions of tumour properties that are necessary for classification.

3. Dimensionality Reduction

The projected features are reduced in dimension and redundancy by PCA. PCA decreases the dimensionality by projecting data onto principal components which capture most of the variance, and in the meantime, preserving critical information, gaining efficiency in computation, and avoiding overfitting.

4. Model Training and Evaluation

Several machine learning classifiers are then trained and tested with the PCA-transformed feature set:

- SVM (Support Vector Machine): Uses kernel functions to improve class separability in higher dimensions. In this work, four types of kernels are evaluated:
  - Linear Kernel – Best for linearly separable data.
  - Polynomial Kernel – Captures interactions up to a certain degree.
  - Quadratic Kernel – A special case of the polynomial kernel.
  - Gaussian Radial Basis Function (GRBF) Kernel – Handles non-linear relationships by mapping inputs into infinite-dimensional space.
- Artificial Neural Network (ANN): Learns complex nonlinear relationships between features and tumor classes through multiple hidden layers and activation functions.
- K-Nearest Neighbors (KNN): Classifies tumor

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- , types based on the closest data points in feature space using distance-based decision-making.
- Random Forest (RF): An ensemble method that combines multiple decision trees to improve classification robustness and reduce overfitting.
- Model performance is evaluated using accuracy, precision, recall, F1-score, and the confusion matrix. Visual tools such as confusion matrix heatmaps are employed to analyse patterns of misclassification and enhance the interpretability of the models.

5. Results and Analysis

After preprocessing and PCA-driven dimensionality reduction, the transformed feature set was tabulated and saved in an Excel file with the train and test data in two different sheets such that the features used during model building could be easily tracked. A few machine learning classifiers were first tried on PCA-transformed features. Out of these, the Support Vector Machine (SVM) classifier worked best at 92.3%, followed by Artificial Neural Network (ANN), at 77.6%, K-Nearest Neighbors (KNN), at 74.4%, and Random Forest (RF), at 70.9%. Bar plots were envisioned for relative performance visualization in Figure 2, and confusion matrices were verified for further exploration of model performance. Statistical values of True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN) were computed for each tumor class to better understand the classifier's behaviour. Table 1 represents the comparison of Accuracy, Precision, Recall, and F1-Score across SVM, ANN, KNN, and RF classifiers.

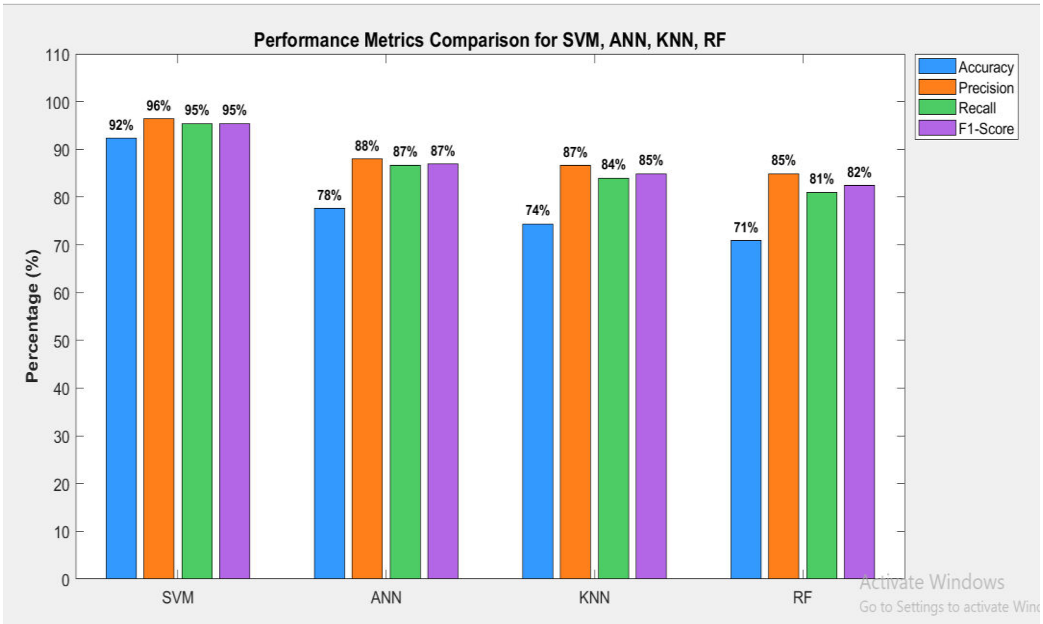

Figure 2: Performance metrics comparison for SVM, ANN, KNN, and RF.

Performance metric for classifiers.	Accuracy	Precision	Recall	F1-Score
SVM	92%	96%	95%	95%
ANN	78%	88%	87%	87%
KNN	74%	87%	84%	85%
RF	71%	85%	81%	82%

Table 1: Comparison of performance metrics for SVM, ANN, KNN, and RF.

Additional experiments were conducted after observing SVM's outstanding performance to assess various kernel functions in SVM models. The Gaussian Radial Basis Function (RBF) kernel showed superior results by achieving 92.3% accuracy and 96.4% precision, combined with 95.4% recall and 95.4% F1-score. The polynomial and quadratic

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kernels demonstrated strong performance with accuracies of 82.7% and 82.1%, while the linear kernel achieved 75.8% accuracy, as shown in Figure 3 and Table 2, which demonstrated its inability to handle complex non-linear decision boundaries. The complete analysis demonstrates that SVM with RBF kernel performs effectively for brain tumor classification and establishes a fundamental basis for additional model enhancement and system deployment.

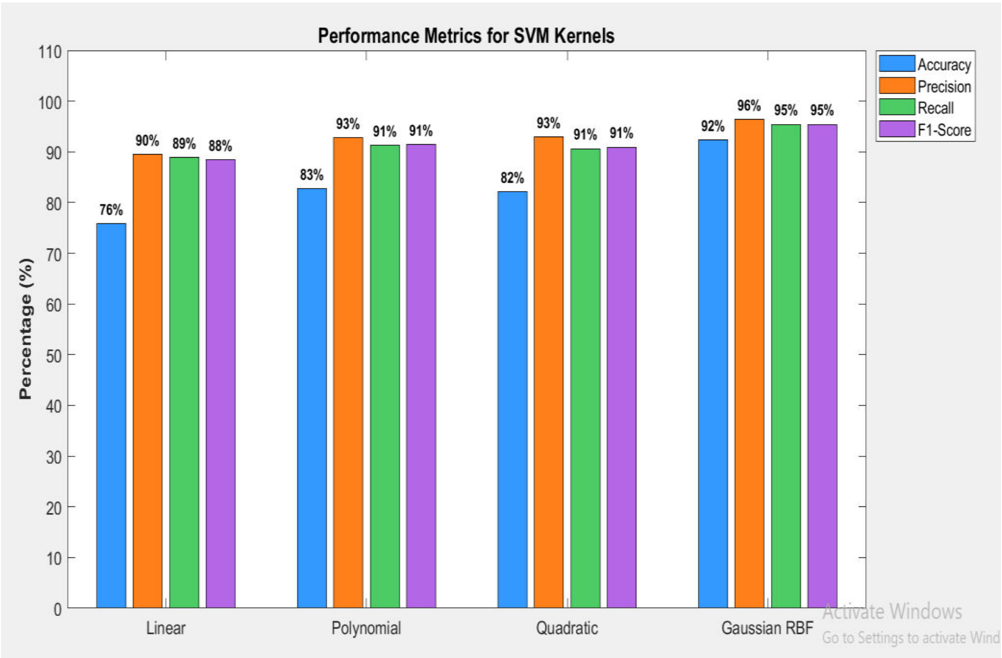

Figure 3: Performance metrics for SVM Kernels

Performance metrics for SVM kernels	Accuracy	Precision	Recall	F1-Score
Linear Kernel	76%	90%	89%	88%
Polynomial Kernel	83%	93%	91%	91%
Quadratic Kernel	82%	93%	91%	91%
RBF Kernel	92%	96%	95%	95%

Table 2: Comparison of performance metrics for SVM Kernels.

Out of all the classification methods tested, the SVM with the Gaussian kernel achieved the highest accuracy for brain tumor classification. To visually assess its performance, Figure 4 clearly shows the model's ability to correctly classify the four tumor types: Glioma, Meningioma, No Tumor, and Pituitary. This confusion matrix highlights the number of true positives and misclassifications for each class, providing a detailed overview of the classifier's strengths and areas where errors occurred. This visualization confirms that the SVM model performs well, especially in distinguishing between tumor types with minimal confusion.

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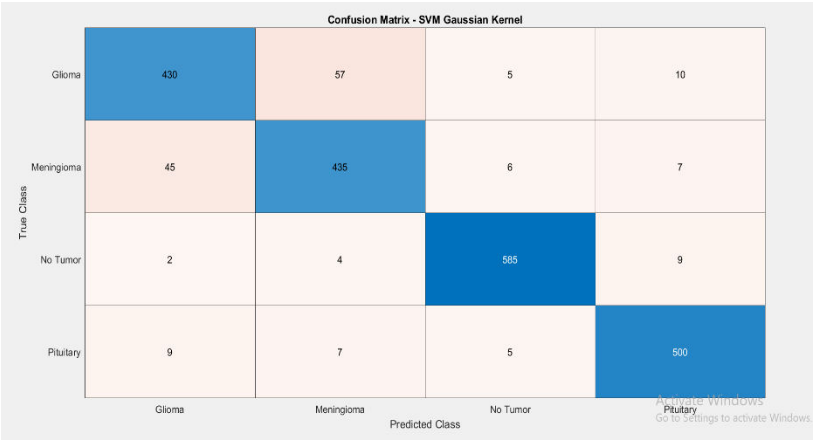

Figure 4: SVM Gaussian Kernel Confusion Metrics

IV. CONCLUSION

The findings of this research suggest that Discrete Wavelet Transform (DWT) and Gray Level Co-occurrence Matrix (GLCM) with Principal Component Analysis (PCA) improved the quality of features created from MR brain images for detecting both frequency and texture features. The Support Vector Machine (SVM) with a Gaussian Radial Basis Function (GRBF) kernel was shown to be the most accurate and robust cutting-edge classifier of the multiple machine learning classifiers tested using the Kaggle Brain Tumor Dataset. The research findings show that DWT-GLCM feature extraction and GRBF-KSVM algorithms have created a valuable framework for automatic detection of brain tumor images that could assist medical professionals with timely and accurate patient diagnoses.

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