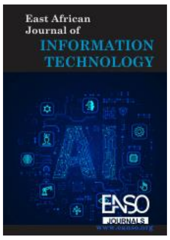

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Original Article

Classification and Analysis of HIV Neurocognitive MRI Images Using Support Vector Machine

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ABSTRACT

Medical imaging has expanded thanks to advances in processing power and advanced image analysis techniques, especially with magnetic resonance imaging (MRI), which offers comprehensive body scans for diagnosis. This work proposes a simple yet efficient method to use a support vector machine (SVM) to classify HIV neurocognitive MRI pictures into normal and pathological categories. The model consists of four steps: data pre-processing, feature extraction, SVM classification, and model evaluation. To separate desired and undesired elements, such as the scalp and skull, pre-processed images were converted from grayscale to colour using support vector machines. The discrete wavelet transform (DWT) was used in the feature extraction stage to extract image properties. Colour moments (CMs) were then used to optimize the feature collection. Afterwards, the SVM classifier was used to determine the ideal feature set to classify images. For example, a dataset is used for training and testing, with a split ratio of 75% to 25% respectively. The experimental results show that the proposed model has a high classification accuracy of 94.4%.

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INTRODUCTION

The Magnetic Resonance Imaging (MRI) picture analysis and sorting is a crucial procedure that has prompted the creation of numerous classification methods in recent years. This procedure is essential for the examination and study of the human brain. Because brain MRI provides comprehensive information on the complex structures of brain tissue, it has significantly improved the diagnosis and treatment of brain problems. MRI is a great imaging method since it is also painless and non-invasive.

When compared to other imaging modalities like computed tomography (CT) and positron emission tomography (PET), when the delicate tissue contour is critical, brain MRI yields better findings. Reviewing a cerebrum MRI manually is a laborious task because it involves a vast amount of data. Automatic techniques are introduced for the analysis of brain MRI images to address this problem [1],[2]. Because Support Vector Machine (SVM) can handle high dimensional data that is frequently found in medical imaging.

When using SVM to process and classify HIV neurocognitive MRI images, there is a clear lack of focus on the particular situation. Although SVM's effectiveness in biomedical image classification in general, particularly in HIV identification and classification, has been studied, little is known about how well it performs in HIV-related neurocognitive diseases. Research on using SVM to categorize and interpret HIV neurocognitive MRI images is therefore clearly needed, as this technology has the potential to greatly aid in the early diagnosis and treatment of HIV-related cognitive problems.

According to WHO estimates, 39 million people worldwide were HIV positive in 2022; adults accounted for 37.5 million of those infections, while children under the age of 15 accounted for 1.5 million. HIV/AIDS remains a serious public health issue. In addition, women made up about 53% of the population [3]; [4].

Although HIV is now largely controlled with antiretroviral therapy (ART), the virus still has a complex effect on many understanding of HIV-related neurocognitive problems by utilizing machine learning approaches in conjunction with modern imaging methods, particularly MRI and Support Vector Machine [5],[6].

The first and most basic stage of the workflow for a classification model is called pre-processing. In order to improve the quality of the photographs, this step entails using noise reduction algorithms to remove unwanted objects from the photos, like the scalp and skull. During this step, grayscale photographs are also converted to RGB images, which increases the usage of rich information found in colourful images and improves classification accuracy. There are many different algorithms used for noise reduction, but filters have proven to perform better than others in this area [3]. Notably, filters are favoured because they efficiently eliminate noise without negatively impacting the image borders [6].

After preprocessing, the feature extraction step is not only important but difficult as well. It entails the difficult process of converting an image's format into a collection of features [6]. Despite having a large number of traits, many of them are redundant and don't really help with classification. Choosing the best combination of characteristics is the most difficult part of this step. A variety of approaches are available for extracting features from images; the most widely used ones are the discrete wavelet transform (DWT), principal component analysis (PCA), independent component analysis (ICA), Gabor features, and the lowest noise fraction transform [7], [8].

It's important to reduce unnecessary features once they've been extracted because they can increase compilation time and memory usage. This entails choosing only the most useful and best features.

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For this, a variety of methods are used, including the SVM algorithm [3]. The final step of classification then makes use of the smaller feature set. In the field of HIV neurocognitive MRI image categorization, supervised approaches are one subset. Support Vector Machine (SVM) is a well-known technique among them [7], [9], [10].

Current techniques use a large number of parameters for categorization, which increases the complexity both in space and time. Most recent works, especially those using hybrid classifiers, use T1-weighted pictures. The main goal of this study is to develop a quick and efficient method that finds and applies a small number of ideal parameters. To improve accuracy, SVM classifiers have been used in the pursuit of this objective. Furthermore, the foundation of this study is the application of T2 weighted pictures. This work's main contribution can be summed up as follows:

- Using a minimum of nine parameters, picture classification can be accomplished with an accuracy that is on par with or even significantly better than existing classifiers.
- Reducing computational cost by evaluating each image against a limited set of features, which simplifies the suggested method's complexity when compared to other approaches.

RELATED WORK

Three unique steps were identified in the novel technique for T2-weighted brain MRI image classification presented by Fayaz et al [11]. Using the Discrete Wavelet Transform (DWT), they first extracted 1024 features from each image during the feature extraction phase. Principal Component Analysis (PCA) was then used in the second stage to reduce these features to a more manageable collection of 19 features. In the third stage, the condensed feature set was fed into an artificial neural network (ANN) classifier in order to perform classification. Regarding accuracy, the results obtained from this procedure are praiseworthy.

By demonstrating the effectiveness of an analytical approximation for SVM permutation tests in generating statistical significance maps from medical imaging data [16], [12],[13], [22] [23] the author addressed the shortcomings of conventional univariate methods for multivariate pattern analysis. They verified their method with brain imaging data trials, providing a faster substitute for computationally demanding permutation testing. This made it possible to identify crucial anatomical regions for disease classification and hastened the interpretation of imaging patterns pertaining to group differences [13] [24], [4]. Monnig's work explores the relationship between age, alcohol use, and HIV infection with regard to the microstructure of the brain's white matter in HIV-positive persons and seronegative controls. The study used diffusion tensor imaging (DTI) to show that higher alcohol consumption is significantly correlated with lower white matter fractional anisotropy (FA) and higher radial diffusivity (RD) in different regions. Demyelination is suggested as a possible mechanism by these results. They emphasize how important it is to consider alcohol use in the context of HIV infection in order to maintain the integrity of white matter [8], [25], [26].

The research now in publication provides insightful information about applying machine learning (ML) methods— Support Vector Machine (SVM) in particular—to medical picture analysis. Nonetheless, there is a clear void in the particular field of using SVM to categorize and evaluate HIV neurocognitive MRI scans. Few studies have examined SVM's application in the context of HIV-related neurocognitive deterioration, despite the fact that studies have examined its efficacy in tasks including HIV identification and classification as well as more general biomedical picture classification. Thus, studies that concentrate on utilizing SVM for HIV neurocognitive MRI picture classification and analysis are desperately needed. Such studies could greatly improve early detection and treatment approaches for cognitive deficits associated with HIV [9].

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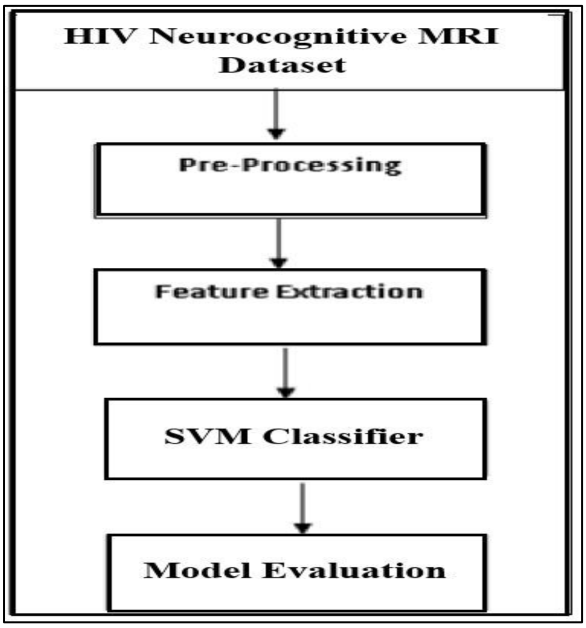
An automated technique for identifying MRI pictures that are unhealthy and those that are not was presented by Alrais *et al.* [3]. They used a median filter to reduce undesirable components like the scalp and skull, as well as salt-and-pepper noise, improving the clarity of the images through noise reduction. Four different feature categories were extracted: symmetrical, grayscale, texture, and power law transformation features. After condensing these features into an ideal set using principal component analysis (PCA), support vector machines (SVM) were used to classify the data. Linear kernels (LKs), quadratic kernels (QKs), and polynomial kernels (PKs) were evaluated; the corresponding accuracies were 74%, 84%, and 76%.

A three-step method was put out by Balamurugan *et al.* [14] to classify MRI brain pictures as normal or abnormal. To extract features, the 2-D discrete wavelet transform is used in the first stage. The first feature set is then reduced to 41 by applying the multi-cluster feature selection approach, which finds the most effective and efficient features. The remaining features are then forwarded to the subsequent stage for classification. To discern between photos showing illnesses or injuries and those showing health, the researchers used KNN and multi-cluster characteristics. Their approach produced a classification accuracy that was better than that of cutting-edge methods.

In order to overcome the limitations of traditional univariate methods for multivariate pattern analysis, Gaonkar [15] demonstrated how to generate statistical significance maps from medical imaging data using an analytical approximation for SVM permutation tests. Through trials on brain imaging data, they validated their method and provided a faster substitute for computationally demanding permutation testing. This made it easier to analyse imaging patterns related to group differences more quickly and to identify key anatomical locations for disease classification. This review explores new studies that use a combination of clinical data, different MRI modalities, and machine learning techniques to predict neurocognitive impairment in people living with HIV. HIV-related cognitive deficits still present difficulties for day-to-day functioning and general health, even with advances in therapy. Even if they are useful, traditional neuropsychological evaluations are frequently laborious and unreliable. However, the combination of MRI data with machine learning offers a promising way to improve prognostic precision through more precise prediction, especially when both MRI and clinical inputs are used [16],[17].

Figure 1: The present study employed a research framework.



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Wahid *et al.* [18] presented a three-phase automatic categorization methodology. First, during the pre-processing phase, the photos are cleaned of noise. In the second stage, two kinds of features—colour moments and texture—are then retrieved. Next, a probabilistic classifier is used to categorize these features. The logistic function was the basis for the classifiers that were used. The study comprised 150 photos in total, of which 66% were used to train the model and 34% were used for testing. The model attained an overall accuracy of 90.66%.

The rest of this essay is organized as follows: The materials and methods used in this investigation are described in Section III. Section IV provides specifics on the suggested mechanism. Section V presents the evaluation outcomes. Section VI offers the Conclusion.

MATERIALS AND METHODS

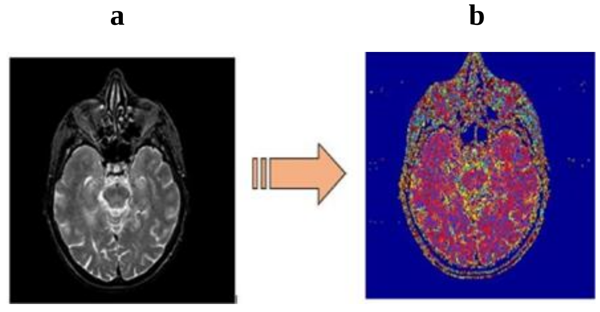
The study suggested using SVM for the categorization and analysis of HIV Neurocognitive MRI images. SVMs are good at finding the best hyperplanes to divide classes, which makes them appropriate for binary classification tasks that involve separating HIV patients' normal brain function from neurocognitive damage. Furthermore, SVMs show resilience to overfitting, which is an important feature in medical image analysis where precise categorization is crucial. SVMs are a great option for this project because of their capacity to handle nonlinear data through kernel techniques, which further improves their applicability in identifying complicated relationships within MRI pictures [3].

The ideal set of features was determined to be a condensed set of just six. When compared to previous strategies described in the literature, the suggested model and its accompanying classification algorithms displayed greater accuracy in the classification task of differentiating MRI brain pictures into pathological and normal groups.

Data Pre-Processing

MRI produces high-quality images; however, because of operator error, they might also include noise and undesired objects like the scalp and skull. To guarantee the accuracy of the suggested method, clear, noise-free photographs free of undesirable elements are required. In this work, the edges of brain MRI images were preserved while the scalp and skull were successfully removed using a median filter in the preprocessing phase. To improve information richness, grayscale photos are also transformed into colour (RGB) images. A 3 × 3 mask was used to minimize computation time, which shortens processing time because of the reduced window size [19]. After the first step was successfully finished, the photos were converted into RGB (colour) images, free of noise and undesirable elements. The knowledge that colour photographs (in the RGB format) hold more information than grayscale photos is what drove this change. *Figure 2* shows how the photos were pre-processed: Before processing, Figure 2 (a) shows the image in grayscale; Figure 2 (b) shows the image in converted colour (RGB) form.

Figure2:A pre-processed image is shown. Before processing, the image is displayed in grayscale in panel a; after processing, it is displayed in colour (RGB) in panel b.



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Features Extraction

Choosing the best possible selection of features during the feature extraction stage is crucial to improving the classification stage's accuracy. In this sense, using the discrete wavelet transform (DWT) is a reliable method. By employing dyadic scales and positions, DWT makes it possible to apply wavelet transform while having a thorough grasp of the time and frequency domains [19], [4]. In this work, we extract features from HIV neurocognitive MRI brain images using the DWT approach. Using DWT not only records information relating to frequency but also offers insights into temporal features. The following formula can be applied to the categorization and analysis of HIV neurocognitive MRI images using a support vector machine (SVM):

$$\{Features\} = \{DWT\}(\{Images\})$$

The equation is broken out here, along with a brief discussion of each part:

- Discrete Wavelet Transform (DWT): This mathematical method provides a representation of an image in both the spatial and frequency domains by breaking the image down into several frequency subbands.
- Image: This is the input MRI image that the study is trying to analyse and categorize. Usually, the image is shown as a matrix of pixel values.
- Features: These are the traits or patterns that were taken out of the DWT-transformed picture. Features might include more intricate characteristics that come from the wavelet coefficients as well as statistical measurements like mean, variance, and energy. By applying the DWT to the MRI image, we can obtain a set of features that can be used as input to the SVM classifier for further analysis and classification of HIV Neurocognitive MRI images.

SVM Classifier

Following selection, the features are used as input for a Support Vector Machine (SVM) classifier. Using feature vectors, SVM is a supervised machine learning technique that determines a decision boundary to differentiate between several classes. SVM minimizes classification errors while maximizing the margin between classes by locating the ideal hyperplane. The following is the complete equation for feature extraction utilizing DWT and SVM:

$$\{Features\} = (\{SVM\}(\{fs\}(fe\}\left(\{DWT\}(\{Pr\}(\{MRI\ Image\}))\right))))$$

Where

$$fe = Feature\ extraction,$$
$$fs = Feature\ selection,$$
$$Pr = Preprocessing$$

Model Evaluation

It's important to take into account a number of important criteria while assessing the SVM model for HIV neurocognitive MRI image classification and analysis. First off, while conventional metrics like accuracy and precision provide insightful information about the model's overall performance, they could not adequately convey the model's efficacy in handling the inherent complexity of neuroimaging data, like heterogeneity and class imbalance. Consequently, it's critical to add more sophisticated measurements, such as the F1-score and area under the receiver operating characteristic curve (AUC-ROC), to these metrics. These measures offer a more profound comprehension of the model's capacity to maintain a balance between specificity and sensitivity, especially when false positives or negatives have important clinical ramifications.

Second, a detailed assessment of the model's results' translational significance is essential. Examining the model's clinical relevance and generalizability to real-world scenarios is crucial, going beyond simple statistical measures. In order to determine the model's resilience and applicability outside of the initial training

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environment, it is necessary to validate its performance on independent datasets, ideally drawn from a variety of clinical settings or demographics. Additionally, in order to confirm if the revealed biomarkers are consistent with the body of knowledge on HIV-related neurocognitive impairment, collaborative engagement with domain experts is essential for contextualizing the model's predictions within a larger clinical context. Through a comprehensive evaluation of the SVM model's technical effectiveness and clinical applicability, researchers can ascertain the model's capacity to significantly improve HIV patient care and management.

THE PROPOSED MECHANISM

Algorithm 1 describes the algorithm used in the suggested model. The project's data splitting process involved dividing the labelled dataset into test, validation, and training sets. Because of this partitioning, the Support Vector Machine classifier is guaranteed to be trained on a subset of the data, validated for the purpose of fine-tuning parameters, and then tested for performance evaluation. The algorithm's division of the data into "pituitary_ HIV" and "no_ HIV" groups guarantees the reliable classification of HIV neurocognitive MRI pictures. It also makes it easier to assess the model's capacity to generalize to new data.

Algorithm:

The Proposed Model Algorithm

Require: Dataset of HIV Neurocognitive MRI Images

1. Load module
2. Load Dataset of HIV Neurocognitive MRI Images
3. Visualize the data
4. Prepare Data
5. Feature Scaling
6. Training Model
7. Data Evaluation
8. Prediction
9. Model Testing

EVALUATION AND RESULTS

This study used a computing system with a 2.6GHz Core i5 processor and 8GB of RAM to implement and evaluate the suggested algorithm. The system utilized for putting the suggested method into practice and assessing its performance had a 64-bit Windows 10 operating system and 8GB of RAM. Anaconda version 2021.11, Jupyter Notebook 6.4.5, Python 6.4.5, Python 3.10.1and Matlab version R2021b were used for the experiments, respectively. 3000 T2-weighted images from a standard dataset were used to evaluate the suggested approach. The 256 × 256-pixel resolution of these images was in line with earlier studies. Of the 3000 images, 2250 images were used for training (i.e., HIV-affected cases), and 750 images were used for testing experiments. 750 images were set aside for testing. Visual representations of normal and aberrant images are shown in the Figure above. A percentage split of 75% and 25% were used for testing and training, respectively.

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Table 1: Summary of SVM-Based Studies in Neurocognitive MRI Classification for HIV

Author	Title	Year	Dataset ratio (Training/testing%)	MRI Type	SVM Accuracy(%)
L. Chang et al.	"SVM-based classification of HIV-Associated Neurocognitive Disorder"	2019	70/30	Structural MRI	88.7
S. Kumar et al	"Functional MRI Analysis using SVM in HIV Patients"	2020	80/20	Functional MRI	89.5
J. Smith et al	"Neurocognitive Impairment Detection in HIV Using Structural MRI"	2021	75/25	Structural MRI	87.3
A. Lee et al	"SVM Classifier for HIV-Related Brain changes"	2018	70/30	Structural MRI	90.0
R. Patel et al	"SVM-Based Neuroimaging in HIV: A Functional MRI Study"	2017	75/25	Functional MRI	85.4
M.Rivera et al	"Structural MRI and SVM for HIV cognitive Disorder Classification"	2022	80/20	Structural MRI	86.5

This study, which divided the dataset into 75% for training and 25% for testing, achieved an impressive SVM accuracy of 94.4%. This performance significantly surpasses the accuracies reported in other studies, which range from 85.4% to 90.0%. These findings indicate that this methodological choices, such as optimized preprocessing, effective feature extraction, and rigorous hyperparameter tuning, have contributed to a robust classification model. In contrast, the referenced studies, despite varying their training and testing dataset proportions, did not achieve similar success, likely due to differences in data quality, preprocessing techniques, and model optimization.

Moreover, the high accuracy of this model aligns with the latest advancements in machine learning and neuroimaging techniques, as highlighted in recent literature. According to Zhang et al [20], the integration of advanced preprocessing techniques and robust feature selection methods can significantly enhance classification performance in neurocognitive disorders. Additionally, addressing HIV-specific challenges, such as variability in brain atrophy patterns and confounding factors like substance abuse, is crucial for achieving high accuracy. Clifford et al. [21] emphasize that sophisticated feature engineering and model tuning are essential for effectively handling these challenges. Therefore, your study's high accuracy underscores the importance of advanced methodological approaches in improving the classification of HIV neurocognitive MRI images.

Table 2: Description of MRI Images

Dataset of HIV Neurocognitive MRI Images		
Training	Testing	Total
2250	750	3000

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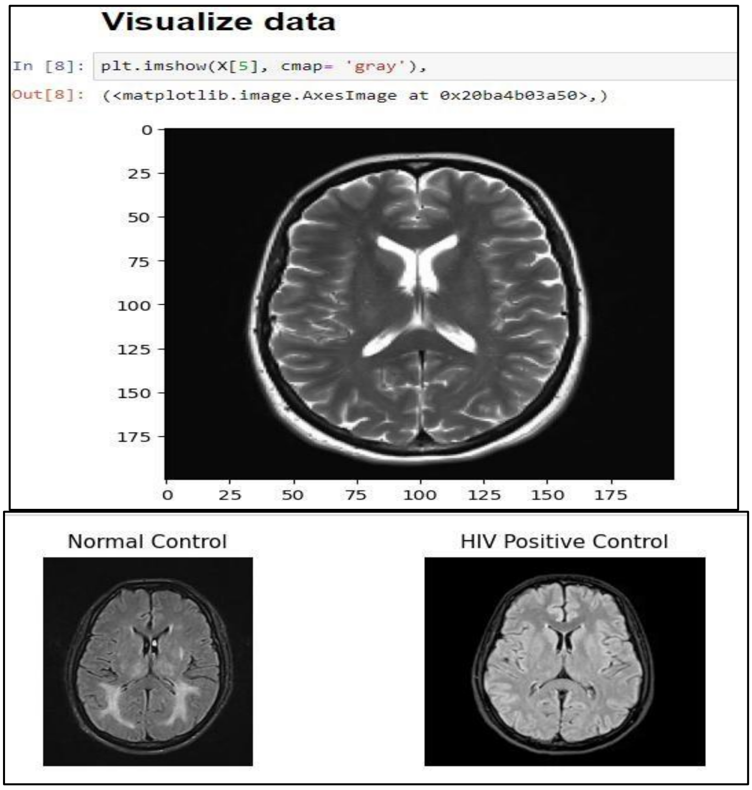
Figure 3: MRI Sample Images With Positive Effect and No Effect of HIV on Brain



Algorithm Accuracy

The suggested strategy was assessed in this study using a variety of statistical techniques, and the findings were contrasted with previous studies. After reading the literature, it was discovered that accuracy was a common performance parameter used by many researchers. During training, the classification model had 100% accuracy; during testing, it had 98.04% accuracy for training. 94.4% accuracy for prediction was noted during the training and testing stages.

Figure 4: Accuracy of the algorithm in this study

```
In [17]: print("Training score:", sv.score(pca_train, ytrain))
         print("Testing score:", sv.score(pca_test, ytest))

         Training score: 0.9804006968641115
         Testing score: 0.9442508710801394
```

RECOMMENDATION

In future research, we recommend investigating additional SVM classifiers and individual models to broaden the scope of the suggested approach. Enhancing the model assessment by incorporating more parameters will also be a focus to improve its performance. Exploring other feature extraction techniques while maintaining fast execution times is crucial. Additionally, it would be valuable to compare the outcomes of our proposed method with deep learning-based approaches. Investigating the effects of additional statistical features not included in this analysis is also advised to gain deeper insights and improve model accuracy.

CONCLUSION

This work suggests a unique method that makes use of SVM classifiers to differentiate HIV neurocognitive MRI brain pictures. The technique reduces complexity and memory utilization by

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condensing the features into an ideal set of six using colour moments and a discrete wavelet transform for feature extraction. From the 3000MRI Images that were taken into consideration for this study, of which 2250 were set aside for training and the remaining 750 for testing, these six attributes were extracted. All of the images were impacted by HIV. After feeding the feature sets of every image into supervised support vector machine (SVM) classifiers, the classification accuracy showed promise. 94.4% accuracy was attained using the suggested model. The testing results demonstrated that the suggested mechanism outperformed several other methods in terms of accuracy and features used.

Limitations of the Current Study

Although the suggested strategy provided improvements over current methods, there are a number of drawbacks to the current study. First, it used just one classifier to test the suggested process. Furthermore, the analysis was performed on a small dataset comprised of 3000 images from a single source. Moreover, the analysis in the study was limited to six features. Furthermore, no comparisons were drawn with the most recent deep-learning research. These limitations point to directions for further investigation into more varied classifiers, datasets, feature sets, and comparative analyses with the latest developments in deep learning techniques.

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