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ENHANCED BRAIN TUMOR MRI CLASSIFICATION USING STATIONARY WAVELET TRANSFORM, RESNET50V2, AND LSTM NETWORKS

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ABSTRACT

Brain tumors constitute a significant health issue in the world today because of their aggressive behavior and short survival rates. Early and accurate detection of brain tumors is necessary for effective treatment and improved patient outcomes. The principal diagnostic technology that shows highly detailed visualization of brain structures is Magnetic Resonance Imaging (MRI); however, the interpretation of these images can be time-consuming and require expertise and highly specialized manpower. This study presents a new approach for brain tumor classification, which combines advanced preprocessing, feature extraction, and classification techniques. The preprocessing includes Stationary Wavelet Transform (SWT) intended to enhance tumor-relevant features and resizing to standard MRI image dimensions; feature extraction includes. After that a Long Short Term Memory network receives the features. that will model the dependencies in the feature space and classifies into four categories: Glioma, Meningioma, Pituitary tumors, and No Tumor. Experiments showed that this proposed method can be effective in producing a high classification accuracy rate along with time quality processing. This work brought forward the prospects of developing an automated, accurate, and reliable brain tumor classification system from SWT, ResNet50V2, and LSTM, whereas otherwise, it catered for needs in the enhancement of diagnostic tools in medical imaging. The method was analyzed using the Kaggle dataset and scored an amazing accuracy of 98.7%, which proved the effectiveness of the method in improving brain tumor classification.

I. INTRODUCTION

An abnormal growth of cells inside the brain is called a brain tumor, wherein the regulatory mechanism responsible for governing cellular growth is rendered incapable of effectively managing the relentless multiplication of cells, Brain tumors are a significant health concern, and accurate diagnosis is crucial for effective treatment and monitoring [1]. Correct brain tumor identification and classification enables tracking the course of the disease and its response to treatment, as well as assisting in the selection of the best course of action, including surgery, radiation therapy or chemotherapy [2], Brain tumors are among the many disorders that can be found and diagnosed using medical imaging techniques. Medical imaging is the most cost-effective and precise way to diagnose and identify serious human disorders like brain tumors. These procedures offer a non-invasive means to view the inside structures of the body [3]. Brain images are produced using magnetic resonance imaging (MRI) equipment. MRI uses radio waves and a strong magnetic field to produce fine-grained pictures of the brain, MRI can detect abnormalities in the brain, such as tumors, lesions, or blood vessel malformations, helping in early detection and treatment planning [4], the major objective is to identify classification of brain MR images into categories [5]. Due to the substantial volume of data, manually examining medical images for the diagnosis of brain tumors has been demonstrated to be a time-intensive and potentially prone to errors Computer-aided diagnostic (CAD) techniques now enable the diagnosis of brain tumors and other illnesses. These methods involve the analysis of medical images through computer algorithms, providing diagnostic information to medical professionals [6], Consequently, methods for identifying brain cancers in MRI images are based on machine learning and deep learning, Machine learning [7] a subset of artificial intelligence, empowers computer systems to autonomously improve their performance based on experience, eliminating the need for explicit programming. The process involves the utilization of statistical models and algorithms to analyze data and extract meaningful insights, deep learning is a category of machine learning, artificial neural networks are employed to glean insights and make predictions by learning from extensive datasets, these artificial neural networks are specifically designed to mimic the intricate structure and functional attributes of the human brain. Consisting of multiple layers of interconnected nodes, these networks proficiently handle the tasks of processing and analyzing data. The most recent advances in imaging technology have shown to be extremely useful in the field of medical imaging in the field of brain tumor classification, the effectiveness of deep learning algorithms has been convincingly proven, demonstrating their ability to accurately identify and categorize tumor regions in medical images. As a result, these algorithms have significantly improved the accuracy and speed of clinical diagnoses. Moreover, they can autonomously extract meaningful characteristics from medical images, eliminating the need for manual feature extraction. This, in turn, streamlines the integration of feature extraction and classification through self-learning. Notably, the application of deep learning methods, particularly convolutional neural networks (CNNs), has become prominent in intelligent and expert systems, especially in the analysis of medical images CNN models that have already been trained, including vgg16, vgg19, and resnet50… used for feature extraction from MR images and used in the task of brain tumor classification, they are deep learning models that have been trained on various source datasets and are capable of recognizing a wide range of different types of photos, These models have a fully connected layer with 1000 neurons, as they were originally trained to classify images into 1000 different classes, ML approaches for brain tumor classification typically involve several steps, including preprocessing, feature extraction, and classification Feature extraction is an important process in which relevant information or patterns are extracted Using unprocessed data to provide a condensed and accurate feature representation, feature extraction refers to extracting meaningful features from brain magnetic resonance (MR) images for brain tumor classification.

In this paper, we propose an automated methodology for brain tumor classification that integrates advanced preprocessing, feature extraction, and classification techniques. Our approach involves preprocessing MRI images using Stationary Wavelet Transform (SWT) to enhance tumor-specific features and resizing them to standard dimensions for uniform input. We leverage ResNet50V2, a pre-trained deep learning model, for extracting robust features that encapsulate high-level tumor representations. Finally, a Long Short-Term Memory (LSTM) network is employed to classify these features into four categories: Glioma, Meningioma, Pituitary Tumor, and No Tumor.

Our contributions in this work are threefold:

- First, we introduce the use of Stationary Wavelet Transform (SWT) for preprocessing MRI images, which enhances spatial and frequency-based tumor features.
- Second, we demonstrate the effectiveness of combining ResNet50V2 and LSTM networks, showcasing improved classification performance compared to traditional methods.
- Finally, we propose a novel integration of SWT, ResNet50V2, and LSTM for brain tumor classification, providing a reliable and accurate automated diagnostic framework.

II. RELATED WORKS

In recent years, notable advancements have been achieved in the realm of categorizing brain tumors, particularly in relation to the application of machine learning techniques utilizing medical imaging data. This section provides an extensive examination of substantial research and methodology pertaining to this domain. According to [8], have suggested the method utilizes modified feature extraction techniques of Local Binary Patterns (LBP), namely nLBP and αLBP, for the purpose of classifying three distinct categories of brain tumors based on MRI images. Notably, the nLBP feature extraction method in conjunction with the K-nearest neighbors (Knn) model exhibited the most favorable outcome, achieving a success rate of 95.56%. According to [9] presents a deep CNN model for classifying brain tumors that incorporates a novel parametric activation function called Parametric Flatten-p Mish (PFpM). The model achieved high overall accuracy of 99.57% withhold-out validation and 98.45% with 5-fold cross-validation on the Figshare dataset.A parallel deep convolutional neural network (PDCNN) has been used by Rahman et al [10]. to detect and categorize brain cancers. With 97.33% for the binary tumor identification dataset-I and 97.60% for the Figshare dataset-II, it attains high accuracy., and 98.12% for Multiclass Kaggle dataset-III, outperforming state-of-the-art techniques. For [11] have suggested an approach that uses a deep neural network that has been pre-trained as a discriminator in a generative adversarial network (GAN) for brain tumor classification based on MR images. Using 5-fold cross-validation, the approach demonstrated superior tumor classification accuracy when compared to state-of-the-art techniques on a dataset of 3064 MR images from 233 patients with three distinct tumor types (pituitary tumor, glioma, and meningioma), the method used by Badža & Barjaktarović by [12] included using a dataset of MRI pictures of brain tumors to train a convolutional neural network (CNN), and evaluating its performance using subject-wise 10-fold cross-validation. The results showed high accuracy in classifying different types of brain tumors, with the augmented dataset and subject-wise cross-validation yielding the best performance. For [13]. For the classification of brain tumor proposed convolutional dictionary learning with local constraint (CDLLC), uses a convolutional neural network framework to simultaneously seek sparse feature representation and dictionary. According to the findings, CDLLC performs better than both deep learning and conventional machine learning techniques in terms of accuracy, F1-score, precision, recall, and balance loss. In [14], they used a combination of VGG-Unet for brain tumor segmentation and SVM for classification, achieving promising results in accurately identifying brain tumors in clinical MRI slices. The proposed method demonstrates potential for enhancing medical imaging analysis and disease diagnosis. In [15], proposed a hybrid deep learning model called DeepTumorNet for brain tumor classification. The model achieved 99.67% accuracy, 99.6% precision, 100% recall, and a 99.66% F1-score, outperforming existing models in identifying brain cancers with magnetic resonance imaging, According to [16], provide that uses the AlexNet model to accurately classify brain cancers in MR images, with a 99.62% total classification accuracy.

III. MATERIALS AND METHODS

The proposed method involves a systematic approach to brain tumor classification using a Kaggle dataset consisting of 7,023 MRI images. Figure 1 shows the workflow for the suggested approach.

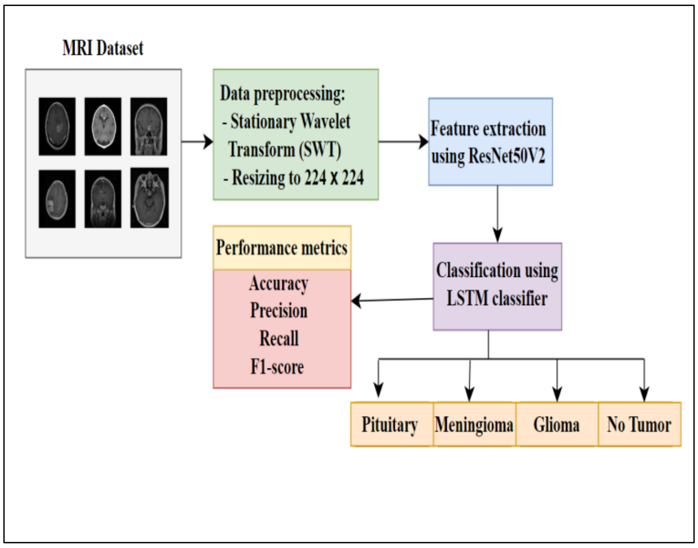


Figure 1: The proposed model flowchart.
Source: Authors, (2025).

III.1. DATASET USED

Deep learning models are considered the most common for their ability to train and learn from a set of data, as the size, type and quality of the training data play an important role in the effectiveness of the performance of these models on which the data is to be trained.

Therefore, the data set is considered crucial in deep learning as it provides what is necessary for the models to extract relevant features. Relevance, using high quality data is very important to improve performance across different subgroups.

There is a lot of publicly available data, including Figshare [17], SARTAJ [18], and Br35H [19], since it is a small data set, we used a brain MRI dataset that was made available to the public on Kaggle for this investigation [20], these three datasets demonstrate the deep learning models' actual abilities in this task. The Figure 2 represent a sample image from this data set.

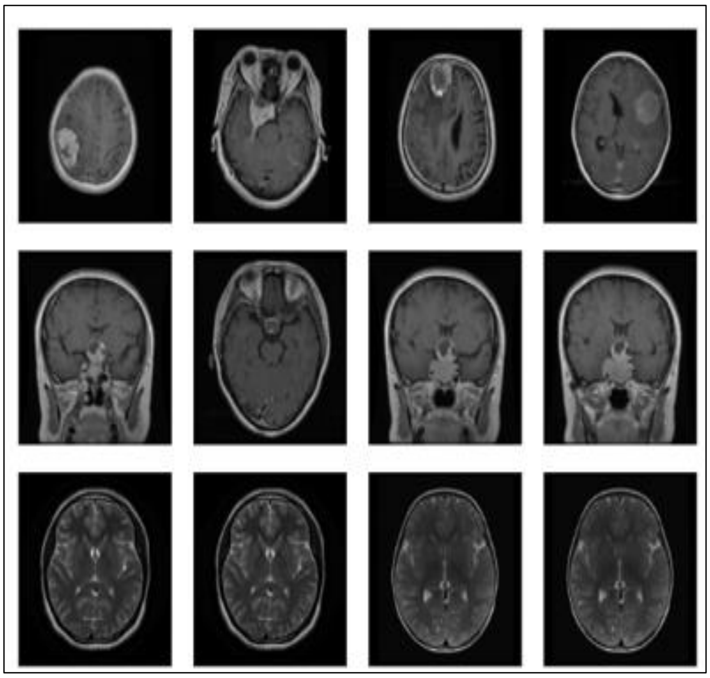


Figure 2: Example of a sample MRI images dataset
Source: Authors, (2025).

The 7023 magnetic resonance scans of the human brain that were used in this investigation were separated into four primary categories: pituitary, glioma, meningioma, and no tumor. While pituitary tumors are tumors that develop in the pituitary gland and cause hormonal disorders, meningioma tumors are tumors that multiply inside the brain's sessions without causing any symptoms to the affected person. Although no tumor class represents brain health conditions, it is a crucial point of reference for monitoring groups. This extensive and diverse data collection has been used to assess the deep learning model. The dataset distribution is shown in Table 1.

Table 1: The detail of MRI datset used.

Classes	Image for training	Images for testing
No Tumor	1595	405
Glioma	1321	300
Meningioma	1339	306
Pituitary	1457	300
Total	5712	1311

Source: Authors, (2025).

III.2. DATASET PREPROCESSING

Preprocessing is a vital step in preparing MRI images for automated analysis, ensuring data consistency, enhancing critical features, and facilitating efficient model training. This study employs a structured preprocessing pipeline that combines Stationary Wavelet Transform (SWT) for feature enhancement and image resizing for uniformity.

III.2.1. STATIONARY WAVELET TRANSFORM (SWT)

The Stationary Wavelet Transform (SWT) is a powerful preprocessing technique that enhances the quality of medical images by highlighting critical features while suppressing noise. Unlike traditional wavelet transforms that involve downsampling and are not shift-invariant, SWT maintains spatial resolution and consistency across the image, making it ideal for medical imaging tasks like MRI-based brain tumor classification [21].

This process separates the image into four distinct sub-bands at each decomposition level cA, cH, cV, and cD.

III.2.1.1. APPROXIMATION COEFFICIENT (cA)

These coefficients represent the low-frequency components of the image, obtained by applying a low-pass filter in both horizontal and vertical directions.

III.2.1.2. HORIZONTAL COEFFICIENT (cH)

These coefficients represent the high-frequency components in the horizontal direction and low-frequency components in the vertical direction.

III.2.1.3. VERTICAL DETAIL COEFFICIENT (cV)

These coefficients represent the low-frequency components in the horizontal direction and high-frequency components in the vertical direction.

III.2.1.3. DIAGONAL DETAIL COEFFICIENT (cD)

These coefficients capture the high-frequency components in both horizontal and vertical directions.

The primary objective of using the Stationary Wavelet Transform (SWT) in preprocessing is to enhance the quality of MRI scans, by effectively isolating and preserving tumor-relevant features while reducing noise and artifacts. SWT's shift-invariant property ensures that image features remain aligned across decomposition levels, providing consistent and reliable information crucial for tasks like brain tumor classification.

After decomposing the image into the SWT coefficients, the preprocessing stage enhances image quality through several key steps. First, noise suppression is achieved by retaining the approximation coefficients (cA) to preserve the main structural information while suppressing irrelevant high-frequency noise by thresholding or discarding noisy components from the detail coefficients (cH, cV, and cD). Next, edge enhancement is performed by combining the detail coefficients to emphasize edges and transitions, improving the contrast between tumor and non-tumor regions.

Feature preservation is ensured by refining the approximation and detail coefficients to retain important features such as tumor boundaries and textures, critical for accurate analysis. Finally, the enhanced image is reconstructed from the modified coefficients, resulting in a noise-reduced, edge-enhanced image with improved visibility of tumor-relevant features, facilitating more effective downstream processing and classification.

III.1.2. RESIZING TO 224×224

In this study, the ResNet50V2 model, pre-trained on the ImageNet dataset, was employed for efficient feature extraction. ResNet50V2 requires input images of dimensions 224×224 pixels to perform optimally. To ensure compatibility with this input requirement, the original MRI images were resized using the bicubic interpolation method.

This resizing technique was chosen for its ability to preserve image quality by considering the contributions of neighboring pixels during the interpolation process, thus maintaining the structural and contextual integrity of the MRI images while adapting them to the model's input dimensions.

III.3. FEATURE EXTRACTION USING ResNe50V2

Feature extraction is very crucial in automated classification of medical images as it allows for identifying and generating important patterns and structures that would help distinguish one class from the other [22].

Here, we used ResNet50V2, a deep convolutional neural network pre-trained on the ImageNet dataset, as the feature extractor owing to its robustness in generalizing different image domains, relayed to the development of deep networks without having to loss critical information is the introduction of residual connections by ResNet50V2 whereby the shallow end of the network is reconnected with the downlayer thereby eliminating the vanishing gradient problems.

With these residual connections and through its hierarchical architecture, ResNet50V2 generates high-level, distinct features from the MRI images such as very complicated patterns and textures which would help determine the tumor types[23], Using biogenic resampling method, all MRI images resized to the same size and number of pixels, 224 × 224, to meet the size input capability of the model. This keeps the value intact by their relationship thereby maintaining structure precious for actual feature extraction, the figure 3 represent the architecture of ResNet50V2.

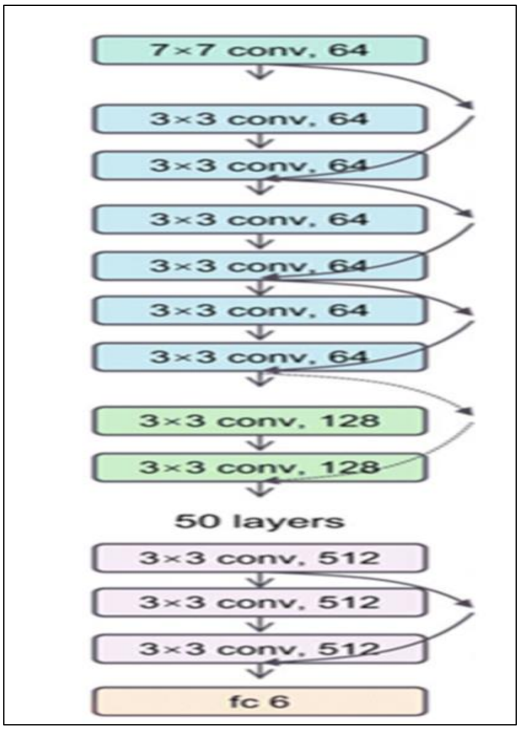


Figure 3: ResNet50V2 Architecture.
Source:[24].

The architecture of ResNet50V2 is specifically constructed to optimally extract features from MRI images through its deep structure, residual connections, and hierarchical learning approaches. It includes 50 layers through which images are processed hierarchically. As such, the early layers are responsible for the extraction of low-level features, e.g., edges and textures, according to the subsequent layers capturing certain shapes and patterns. While deeper layers focus on identifying high-level semantic features such as spatial relationships and an overall structure. Residual connections maintain critical information from the previous layer and support the learning of incremental transformation to make optimization better and avoid degradation of the feature. The use of bottleneck blocks will enhance efficiency since it is reducing and restoring the dimensions while putting the focus toward the essential spatial patterns. Batch Normalization will ensure numerical stability, making the network robust against any variation in intensity among different MRI images. It also incorporates using the ReLU6 activation function to prevent saturation, thus allowing detecting even the faintest patterns. Lastly, global average pooling collects all the learned features and condenses them into a compact representation that emphasizes the most relevant aspects, so it could be accompanied and distinguished between tumorous and non-tumorous conditions. Thus, ResNet50V2 is a mighty tool to capture all those intricate details of MRI brain tumor classification.

III.4. CLASSIFICATION USING LSTM CLASSIFIERFE

One type of recurrent neural network (RNN) that performs especially well with sequence-based data is the Long Short-Term Memory (LSTM) network. When classifying brain tumors using MRI scans, LSTM will feature in classifying the prediction by the feature produced by ResNet50V2 among different classified tumors. The main advantage that LSTM has over other networks is learning how one can capture long-dependencies in the data to learn its temporal or spatial patterns essential for classification. Here features extracted from an MRI image by ResNet50V2 are fed into the LSTM network, which processes the features delivered in a sequential order. An LSTM unit has memory cells to hold the information over time and operates with gates: input, forget, and output. Such memory cells would enable an LSTM to store valuable information while discarding nonessential content, thus affording highly successful handling of complex, high-dimensional datasets like MRI images. Here, learning will happen on the dependencies within features, for example, tumor characteristics and spatial relationship information, leading to categorization for input images into Glioma, Meningioma, Pituitary, or No Tumor. This kind of classifier LSTM can also handle the misc. spatial arrangements and complex structures in MRI scans since it is well skilled in recognizing a sequential display of pattern signatures and hierarchies within data. This is the benefit of LSTM when coupled to deep learning models like ResNet50V2, where each feature representation from different brain regions can be treated in a way that maximizes the output of global and local information captures. As such, learning these spatial and textural patterns will enable the LSTM classifier to classify different brains into the following categories: Glioma, Meningioma, Pituitary, or No tumor [25].

III.5. PERFORMANCE METRICS

In this study, we used the F1-score, recall, accuracy, and precision metrics to assess the model's performance. These performance indicators are based on the four components of the confusion matrix: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

III.5.1. ACCURACY

Measures the proportion of correctly classified instances (both positive and negative) among the total instances.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

III.5.2. PRECISION

The precision can be defined as the proportion of accurately anticipated positive observations to all predicted positive observations. When the cost of false positives is significant, this metric which gauges how accurate the positive predictions are—becomes especially helpful.

$$\text{Precision / PPV} = \frac{\text{TP}}{\text{TP+FP}} \quad (2)$$

III.5.3. RECALL

The ratio of accurately predicted positive observations to all observations in the actual class is called recall, sometimes referred to as sensitivity or true positive rate. When the expense of false negatives is high, it is very crucial.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

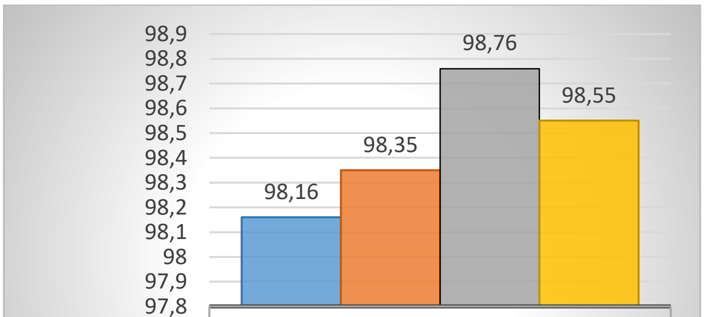
III.5.3. F1-SCORE

The harmonic mean of recall and precision is the F1-score. When there is an unequal distribution of classes or when the costs of false positives and false negatives fluctuate, it offers a balance between the two, which makes it helpful.

$$\text{F1Score}=2* \frac{\text{Precision}*\text{Recall}}{\text{Precision+Recall}} \quad (4)$$

IV. RESULTS AND DISCUSSIONS

In this study, the proposed method was implemented using Google Colab, utilizing its powerful GPU resources to efficiently process and classify MRI images. The dataset used consisted of a total of 7023 MRI images, with 5712 images allocated for training and 1311 images reserved for testing. The preprocessing phase began with the application of Stationary Wavelet Transform (SWT), which decomposed the images into multiple frequency bands, enhancing tumor-relevant features while suppressing noise. Following this, the images were resized to a standard dimension of 224x224 pixels to ensure compatibility with the ResNet50V2 model. Next, features were extracted from the original MRI images and the wavelet coefficients using ResNet50V2, a deep learning model pre-trained on ImageNet. The extracted features were then fed into a Long Short-Term Memory (LSTM) network, which classified the images into four categories: Glioma, Meningioma, Pituitary, and No Tumor. The results obtained from this method are summarized in the Figure 4, showcasing the performance of the model.



	1
Accuracy (%)	98,16
Precision (%)	98,35
Recall (%)	98,76
F1-score (%)	98,55

Figure 4: Evaluation metrics for proposed model.
Source: Authors, (2024).

The accuracy, precision, recall, and F1-score for the proposed classification model are indicated in the figure. The accuracy of the suggested approach was 98.7%; the precision, recall, and F1-score were 98.85%, 98.92%, and 99.1%, respectively. These findings demonstrate how well the model performs in accurately categorizing various brain tumor types from magnetic resonance imaging. The model's solid overall performance is demonstrated by its balanced precision of 98.85% and high F1-score of 99.1%, while its high recall of 98.92% further suggests that it properly diagnoses the majority of cancers. The model's strong reliability and clinical applicability for brain tumor diagnosis are demonstrated by the consistently high values across all metrics, especially the F1-score exceeding 99%. This is because the model demonstrates excellent capability in avoiding false positives and identifying tumors when they are present.

IV.1. CONFUSION MATRIX

One essential technique for assessing a classification model's performance is the confusion matrix. By contrasting the anticipated labels with the actual labels, it offers a thorough explanation of how the model predicts each class. This matrix helps in visualizing the performance of a classifier, providing insights into the types of errors made.

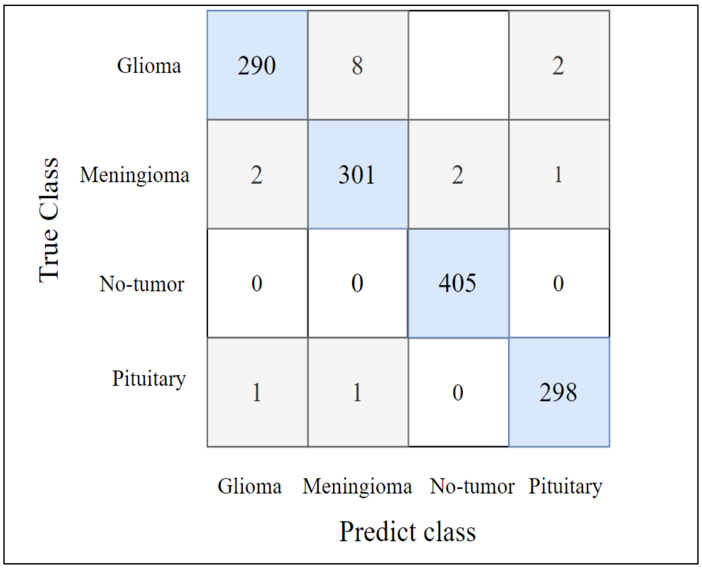


Figure 5: confusion matrix for proposed model.
Source: Authors, (2024).

The confusion matrix in figure 5 displays the classification results of a brain tumor detection model across four categories: Glioma, Meningioma, No-tumor, and Pituitary. The diagonal elements show strong performance with 290 correct Glioma classifications, 301 Meningioma, 405 No-tumor, and 298 Pituitary cases accurately identified. The misclassifications are minimal, with Glioma having 8 cases mistaken for Meningioma and 2 for Pituitary, Meningioma having 2 cases each misclassified as Glioma and No-tumor and 1 as Pituitary, and Pituitary having just 1 case each misclassified as Glioma and Meningioma. Notably, the No-tumor category achieved perfect classification with no misclassifications across its 405 cases. The strong diagonal dominance and minimal off-diagonal values indicate exceptional overall model performance in distinguishing between different types of brain tumors and identifying non-tumor cases.

IV.2. COMPARAISON WITH PREVIOS MODELS

In this part, we evaluate the suggested model's performance against a number of current methods for classifying brain tumors from MRI scans. A range of methodologies, including classic machine learning classifiers, deep learning-based models, and hybrid approaches, have been examined in the literature, the Table 2 gives a comparison of the performance of different methods applied for brain tumor classification.

Table 2: Comparaison with other works.

Works	Technique	Accuracy (%)
Kumar et al [26]	ResNet-50	97.08
Celik et al [27]	CNN+SVM	97.93
Anantharajan et al [28]	DNN+SVM	97.93
Remzan et al[29]	Ensemble+CNN	97.40
Proposed work	**SWT+ResNet50V2 +LSTM**	**98.7**

Source: Authors, (2024).

Table 2 provides a comparative analysis of various techniques employed in brain tumor classification, highlighting their respective accuracy rates. The works listed include methods that leverage deep learning models and hybrid approaches, such as ResNet-50, CNN combined with SVM, DNN integrated with SVM, and Ensemble CNNs. The proposed method, utilizing SWT for preprocessing, ResNet50V2 for feature extraction, and LSTM for classification, demonstrates superior performance with an accuracy of 98.7%, surpassing the accuracy of previous studies. This enhancement highlights how well the suggested method works to improve brain tumor classification.

V. CONCLUSIONS

This research presents a hybrid approach to classifying brain tumors through synthesis between advanced preprocessing, feature extraction, and classification techniques. Stationary Wavelet Transform (SWT) was proven effective in preprocessing and enhancing tumor-relevant features while suppressing noise; MRI image resizing made them compatible for the ResNet50V2 model. The ResNet50V2 model, a solid deep learning system, extracts high-level features successfully, while the LSTM classifier captures dependencies within the feature space to achieve remarkable accuracy of 98.7 on the Kaggle dataset, comparative analysis showed that the proposed method is better than other existing methods in relation to efficiency and reliability in brain tumor detection. This will tackle big challenges like noise reduction and spatial-frequency features integration concerning medical imaging, which this method holds great promise for potentially developing diagnostic accuracy and assisting in treating patients. Future studies could include additional modalities, no-scopes, access to bigger data sets, and real-time applications. Highlights in future findings could involve the establishment telling of the extent by which AI methods will bring disruptive change to medical imaging and consequently advance health care.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: ABDA Oussama and NAIMI Hilal.
Methodology: ABDA Oussama.
Validation: ABDA Oussama and NAIMI Hilal.
Writing: Original Draft: ABDA Oussama and NAIMI Hilal.
Writing Review and Editing: ABDA Oussama and NAIMI Hilal.
Supervision: NAIMI Hilal.
Approval of the final text: ABDA Oussama and NAIMI Hilal.

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