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An Innovative Data-Driven Technique for Identifying Brain Disorders Using a Combined Wavelet Transform Method

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Abstract:

Feature extraction is a vital technique within the fields of machine learning and data mining, especially when it comes to image analysis and classification. It involves isolating the most significant features from an image, which play a crucial role in enabling accurate categorization. As a fundamental pre-processing stage, the efficiency of any classification algorithm is highly influenced by the quality and relevance of the extracted numerical features that represent the image data. This study presents a combined wavelet-based one feature extraction method for identifying abnormalities in the brain using MRI data is the Discrete Wavelet Transform (DWT). The investigation specifically focuses on transaxial plane brain images—one of the primary anatomical orientations along with sagittal and coronal views. To enhance feature representation, the approach integrates two types of wavelet functions: Haar and Biorthogonal 1.3. These wavelets are applied in a two-dimensional space to extract significant image details. The features derived from both wavelets are merged into a single feature matrix, which serves as the input for classification. For the classification task, Support Vector Machine (SVM) models with both linear and polynomial kernels are employed. The performance of this integrated feature extraction approach is benchmarked against several standard machine learning algorithms, including Multi-Layer Probabilistic Neural Network (MLPNN), Naïve Bayes, and Logistic Regression. A comparative analysis with previous techniques from the literature are also used. The suggested DWT-based approach, according to the results combined with the SVM using a polynomial kernel achieves up to a 10% improvement in classification performance over other techniques. To guarantee a thorough assessment, the model's efficacy is gauged utilizing indicators such accuracy, precision, recall, and F1-score.

Keywords: *Feature extraction; Discrete Wavelet Transform; Support Vector Machine (SVM), Multi-Layer Perceptron Neural Network (MLPNN), Gaussian Naïve Bayesian Network and Logistic Regression*

1. Introduction

The development and application of computational models in medical image analysis have significantly advanced diagnostic and interventional procedures. Medical image processing, in particular, has become a highly effective tool for rapidly and accurately identifying various diseases [1] [4]. Studies by Fukuma et al. (2016) and Liu et al. (2016) highlight how these technologies support clinicians in interpreting medical scans with greater precision. By leveraging the full potential of image-based data, diagnostic systems can achieve enhanced accuracy, as noted by Zhu et al. (2017) and Jyothi et al. (2016)[2]. Consequently, the scientific community continues to invest considerable effort in advancing technologies for medical image analysis.

Two of the most fundamental challenges in this field are image segmentation and feature extraction [7]. These steps are vital for constructing dependable and precise computer-aided diagnostic (CAD) systems (Zhu et al., 2017[3]; Jyothi et al., 2016; Nayak et al., 2016). Feature extraction, a core component of finding significant patterns or characteristics in a picture that are necessary for precise classification is made possible by both data mining and machine learning[5]. As stated by Jyothi et al.[6] (2016) and Nayak et al. (2016), this process is a critical pre-processing step that heavily influences the performance of classification models by focusing on numerically significant data attributes.

Generally, feature extraction entails developing a reduced set of variables or descriptors that retain the key information in the original image [8] [11]. This reduction not only boosts the computational efficiency of classifiers but also minimizes overfitting, helping models generalize more effectively to unseen data Ge et al. (2016), Gedik et al. (2016), and Nayak et

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The primary aim of computer-aided analysis in medical imaging is to create accurate and efficient machine learning classifiers for identifying brain disorders Medical imaging methods like Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are commonly used for capturing diagnostic images (Gedik et al., 2016; Jaiswal et al., 2017; D'Angelo et al., 2016)[9]. While these images can reveal pathological conditions, expert interpretation is often required. The objective of this study is to automate the detection of brain abnormalities using data mining and medical image analysis using machine learning techniques[12][14].

The process begins with image enhancement, noise reduction, and feature extraction. Following this, classification algorithms are applied to identify any disorders present in the scans. Brain tumor detection presents a complex challenge due to variability in tumor shape, size, location, and intensity [10] [13]. MRI is widely preferred for its capability to distinguish tumor characteristics with high clarity, particularly when evaluating statistical, texture-based, and symmetry features (Zhao et al., 2016).

Various feature extraction techniques have been applied in medical imaging, including Principal Component Analysis (PCA) (Yu et al., 2014; Park et al., 2009), Independent Component Analysis (ICA) (Spurek et al., 2017; Eugene et al., 2012), Factor Analysis (FA) (Ivancevic et al., 2003)[15], and Linear Discriminant Analysis (LDA) (Zhou et al., 2013; Ghassabeh et al.). Additionally, hybrid approaches have been introduced to further optimize performance [17].

This paper introduces a novel dimensionality reduction-based feature extraction method that utilizes the Discrete Wavelet Transform (DWT) [16]. The approach combines the strengths of two wavelet functions—Haar and Biorthogonal 1.3—into an Integrated Discrete Wavelet Transform (IDWT), as supported by prior work from Bruce et al. (2002), Mohideen et al. (2008), Gupta et al. (2015), and Lai et al.[18][20] (2010). This method transforms the original MRI image into a compressed set of features that retain essential information, allowing for more efficient and successful classification than utilizing the unprocessed image data.

The classification performance of this Support Vector Machine (SVM) is used to assess the feature extraction technique. Classifier, referencing works by Tanoori Li and colleagues (2016), Yu-ting and colleagues (2011), and et al. (2011)[19]. It is also compared against other widely-used classifiers, including Multi-Layer Perceptron Neural Network (MLPNN) (Idris et al., 2011), Gaussian Naïve Bayes (NB) (Xin et al., 2008), and Logistic Regression (Khursid et al., 2015). Performance evaluation is carried out using standard metrics: accuracy, precision, recall, and F1-score, as defined by Powers et al. (2011) [22] [26]. Among all tested models, the SVM with a polynomial kernel consistently achieved the best performance. While SVM with a linear kernel and Logistic Regression produced similar results, they both outperformed Gaussian NB and MLPNN in terms of classification effectiveness [21].

The rest of the paper has been organized into five sections. **Section 2** presents a comprehensive review of wavelet-based feature extraction methods for medical imaging. **Section 3** details the experimental methodology used in this research. **Section 4** discusses the experimental results and includes a schematic representation of the proposed IDWT model and its working mechanism. **Section 5** focuses on result analysis, validation, and parameter tuning. **Section 6** concludes the study with final observations and potential directions for future research.

2. Related work

The increasing reliance on computer-aided diagnosis (CAD) systems in radiology is transforming medical diagnostics by providing faster and more accurate results [23]. These systems reduce the burden on radiologists by automating routine diagnostic tasks, thereby enabling more consistent evaluations. The typical structure of CAD systems involves three primary stages: pattern recognition from images, performance evaluation, and final implementation [24]. These, in turn, are supported by three computational steps—pre-processing (including feature extraction), classification, and validation.

Numerous feature extraction methods have surfaced in recent years, each having a unique combination of advantages and

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characteristics from input images to build effective classification models [27] [29]. Traditional techniques like Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA), and Factor Analysis (FA) have been widely utilized to extract primary features and discriminative patterns from image information from several sources, including Park et al. (2009), Spurek et al. (2017), Eugene et al. (2012), Ivancevic et al. (2003), Zhou et al. (2013), Ghassabeh et al., and Yu et al. (2014)[28].

Unlike PCA or ICA, which focus on uncorrelated or statistically independent components, wavelet transforms such as the Discrete Wavelet Transform (DWT) offer an ability to extract localized, multi-resolution features that capture fine-grained details in images [30]. Due to their irregular and asymmetric properties, wavelets are effective in identifying trends (approximation coefficients) and abrupt variations (detail coefficients), making them particularly useful in medical image analysis (Bruce et al., 2002; Mohideen et al., 2008; Gupta et al., 2015; Lai et al., 2010)[33].

In the present study, DWT serves as the foundation of the proposed feature extraction model, and a comprehensive review of DWT-based methods in medical imaging has been conducted. For example, Nayak et al. (2016) introduced a two-dimensional DWT method combined with AdaBoost and Random Forest classifiers [32]. After extracting features from brain MRIs using DWT, the authors applied probabilistic PCA for dimensionality reduction and constructed a robust feature vector for classification [35].

Karthik et al. (2017) explored a multi-scale analysis using discrete curvelet transforms to detect strokes in MRI scans. Their approach extracted statistical features [31] (e.g., mean, skewness, standard deviation) from different scales and directions and used SVM to evaluate classification performance.

Demirhan et al. (2011) proposed a hybrid method combining Stationary Wavelet Transform (SWT) with Self-Organizing Maps (SOM) and Learning Vector Quantization (LVQ) for segmentation and labeling of MR images [34]. SWT captured multiresolution texture details, while SOM and LVQ were used for automated segmentation. The model's functionality was confirmed using the Tanimoto similarity index, showing high agreement with manual segmentations [36][38].

Another notable approach is by Arizmendi et al. (2012), who developed a hybrid system using DWT and Bayesian Neural Networks for classifying brain tumors from MRI data [37]. They implemented a moving window variance analysis or PCA for dimensionality reduction after pre-processing with DWT [39].

Similarly, Moghaada Nejad et al. (2011) proposed a feature extraction framework using wavelet-radon transforms in conjunction with dynamic neural networks [40]. Their system achieved a classification accuracy of 99% and outperformed static neural networks.

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Sharma et al. (2017) used the analytical time-frequency flexible wavelet transform (ATTFFWT) to decompose EEG signals. was employed, together with fractal dimension analysis and least square SVM classification[42][45]. This method achieved 100% accuracy in detecting epileptic seizures [41].

Chaplot et al. (2006) proposed a classification framework combining wavelet features with both SVM and neural network-based Self-Organizing Maps (SOM), reporting 98% accuracy with SVM and 94% with SOM [43].

Beura et al. (2015) applied 2D DWT to detect gray-level patterns in breast cancer detection, achieving 98% accuracy using a Backpropagation Neural Network (BPNN). El-Dahshan et al. (2010) combined PCA, DWT, and BPNN into a hybrid classification framework for brain images, featuring classification accuracy between 97% and 98% [44].

Xu et al. (2016) introduced a multimodal image fusion technique using Discrete Fractional Wavelet Transform (DFRWT), merging correlated subband coefficients with a weighted regional variance rule. The fused images were evaluated using standard deviation and mutual information metrics.

A classification model based on wavelet entropy and probabilistic neural networks was created by Saritha et al. (2013). Networks. Their system achieved 100% accuracy using spider web plots for feature visualization and DWT for entropy-based feature extraction [45].

Canales-Rodriguez et al. (2013) proposed a wavelet-based morphometry framework for gray matter analysis, employing voxel-based approaches for structural evaluation.

Das et al. (2013) created a classification model using multi-scale image analysis, combining PCA for feature reduction and LS-SVM for classification [46]. Their model also leveraged the ripplet transform, which effectively represents 2D singularities along multiple curved directions, enhancing image representation.

Zhang et al. (2010) introduced adaptive chaotic Particle Swarm Optimization (PSO) as a classification method for brain images combined with forward neural networks (FNN) [41]. Feature extraction was carried out using transform techniques, followed by PCA for dimensionality reduction. PSO was then used to optimize the neural network parameters, resulting in an accuracy of 98.75%.

El-Dahshan et al. (2014) also reviewed CAD systems for brain tumor diagnosis, using PCA for feature selection, DWT for segmentation and a neural network connected to a feedback pulse for feature extraction. Grouping was performed using a feedforward neural network, achieving 99% accuracy [44].

Wang et al. (2015) presented PSO and artificial bee colony optimization are used in this hybrid categorization model, and feedforward neural networks [35]. They used SWT for dimensionality reduction and PCA for feature extraction. Their model achieved 99.45% overall accuracy, 99.37% sensitivity, and perfect precision and specificity [44].

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Our proposed Integrated Discrete Wavelet Transform (IDWT) model draws inspiration from the methodologies discussed in the works of Beura et al. (2015), El-Dahshan et al. (2010, 2014), Saritha et al. (2013), Das et al. (2013), Zhang wang and colleagues (2015) and et al. (2010) [27]. These studies have shown that different DWT variants are effective. in image classification tasks. To validate our approach, we benchmarked the performance of the IDWT model against these established techniques, evaluating parameters such F1-score, recall, accuracy, and precision.

This section outlines the fundamental methodologies employed for conducting experiments and validating the proposed model.

3.1 Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) is a widely used technique for reducing the dimensionality of image data by converting pixel information into a set of wavelet coefficients. Using this technique, the image is transformed into a new domain where key features are easier to identify, aiding in further processing such as classification.

In essence, DWT analyses the image by projecting it onto a set of discrete, orthogonal wavelet basis functions. Each coefficient in the transformed output represents the correlation (or dot product) between the input image signal and a specific wavelet function. These coefficients capture both frequency and spatial information at various resolutions, making DWT especially effective for image analysis tasks.

Mathematically, the transform involves computing the inner product of the image signal with a set of discretely sampled wavelet functions. The resulting values, known as wavelet coefficients, represent different levels of detail and approximation in the image and can be expressed as follows (Equation 1):

(Here you can insert the mathematical formula, labeled as Equation 1)

The transform enables effective data compression and feature extraction by isolating important image characteristics, which are crucial for tasks such as classification and pattern recognition (Bruce et al., 2002).

$$Wf(j,k) = \sum_{x=0}^{N-1} f(n).\varphi^*_{J,K}(n), \qquad (1)$$

Where, $Wf(j,k)$ f(n) is a sequence of length N, and is a DWT coefficient. The phrase $\varphi_{j,k}(n) = \frac{1}{\sqrt{s_0^j}}\varphi\left(\frac{n-s_0^j.k}{s_0^j}\right)$ is the wavelet premise that has been critiqued; where s_0^j is the scale's critiqued version, and s_0^j In the Discrete Wavelet Transform (DWT), the **translation parameter** plays a critical role in determining the position of the wavelet function as it moves across the signal. To perform DWT, two key parameters are essential: choosing a suitable mother wavelet and the MMM for the decomposition level. Decomposition level refers to how many times the input signal is broken down and is determined by both the length of the chosen wavelet filter and the original signal's length. Mathematically, the maximum number of decomposition levels can be approximated using the formula:

$$M=\log2(N)$$

Where N is the total number of samples or the input signal's length.

The Haar wavelet's low-pass and high-pass filters, the most basic type of wavelet transform, have both two lengths. This short filter length allows deeper decomposition levels compared to more complex wavelets such as Daubechies, where

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the filter lengths are longer, resulting in fewer decomposition levels for the same signal length.

Unlike multi-scale representations such as Gaussian and Laplacian pyramids—which tend to generate redundant representations—DWT offers a **non-redundant** representation of image data. This makes it superior in terms of spatial and frequency localization, offering more compact and informative feature representation (Mohideen et al., 2008).

The Haar wavelet transform operates by grouping pairs of input values and computing their sums and differences. The sums are used to represent the next level of approximation, while the differences capture the detailed variations. This procedure is repeated recursively, effectively compressing the signal while preserving essential structural features. The result is a set of detail coefficients and approximation values that retain key information with minimal storage, making Haar suitable for applications involving image compression and feature extraction (Gupta et al., 2015).

The Daubechies wavelet family follows a similar principle but involves more complex filter coefficients. It computes averages and differences through scalar products with carefully designed scaling functions and wavelets. These wavelets offer smoother and more sophisticated feature capture compared to Haar.

At any level of decomposition, DWT maintains a consistent data structure across resolutions, which supports multi-resolution analysis of images while retaining the original signal's significant characteristics (Lai et al., 2010).

3.2 SVM and its kernel functions

SVM is a supervised learning algorithm used for data classification Cortes Cortes *et al.* (1995), Hsu, Chih-Wei *et al.* (2002), Press William H *et al.* (2007) which classifies data in large datasets by identifying separating surface. Separating surface can be linear or non-linear separating surface in the input space of a dataset. Given a training set with label pairs (u_i, y_i), $i = 1, \dots, n$ where $u_i \in \Re^n$ and, $y \in \{profit, loss\}^i$, SVM requires solution of the following optimization problem (2).

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \xi_i$$

Subject to: $y_i(w^T\Phi(u_i) + b \geq 1 - \xi_i, \xi_i \geq 0.$ (2)

Where, decision function is given by (3).

$$p = sgn(\textstyle\sum_{i=1}^{n} y_i \alpha_i K(x_i, x) + \rho) \quad (3)$$

Each training vector ui is projected by the use of a mapping function into a higher-dimensional feature space ϕ. The classification boundary, or decision surface, is defined by Support vectors are a subset of these vectors, which are critical in determining the optimal separating hyperplane. The parameter C>0 serves as a regularization term, controlling the trade-off between maximizing the margin and minimizing the classification error.

Support Vector Machine (SVM) creates one or more hyperplanes—referred to as functional margins in this high-dimensional space to separate the data into distinct classes. In many real-world cases, the data cannot be separated linearly in its original feature space. To address this issue, a **kernel function** is used to transform the

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k(ui,uj)≡ϕ(ui)Tϕ(uj)

data into a higher-dimensional space, making a linear separation possible. That change is defined by the kernel function:
Here, k(ui,uj) calculates the dot product between the mapped feature vectors ϕ(ui) and ϕ(uj) in the new space.

SVM models can be trained using different kernel functions, which are introduced and defined in Equations (4), (5), and (6) to suit different types of data distributions and classification needs.

(a) *Linear kernel*: $(u_i, u_j) = u_i^T u_j$, (4)

(b) *Polynomial kernel*: $k(u_i, u_j) = (\gamma u_i^T u_j + r)^d, \gamma > 0$, and (5)

(c) *Radial Basis kernel (RBF)*: $k(u_i, u_j) = exp(-\gamma \parallel u_i - u_j \parallel^2), \gamma > 0.$ (6)

Here, $C, \gamma, r,$ and d are initialized based on the characteristics of the dataset being used. Selecting the optimal values for these parameters often depends on the size and complexity of the training data. Support Vector Machines (SVMs) can be configured for both **linear classification**, suitable for datasets that are linearly separable, and **non-linear classification**, which handles more complex data distributions that cannot be separated by a straight line in the original feature space. One of the key advantages of SVM is its relatively straightforward training process, as it avoids the issue of getting trapped in local minima—a common problem in neural network models. Additionally, SVM is well-suited for high-dimensional data and allows for a clear balance between model complexity and classification error, which can be managed through the regularization parameter C. This makes SVM a powerful and flexible choice for both simple and complex classification tasks.

3.3 Performance evaluation measures

This section outlines the fundamental metrics used to evaluate the effectiveness of a classification model. These metrics help determine how accurately the classifier performs its intended task. The primary tool for assessing classification performance is the **confusion matrix**, a 2×2 table that categorizes predictions into four outcomes:

- **True Positives (TP)**: Cases where the model correctly identifies a positive instance (e.g., detecting a disease when it is actually present).
- **False Positives (FP)**: Cases where the model incorrectly predicts a positive instance (e.g., diagnosing a disease when the patient is healthy).
- **False Negatives (FN)**: Instances where the model fails to detect a positive case (e.g., missing a diagnosis of a real disease).
- **True Negatives (TN)**: Correctly identified negative instances (e.g., correctly recognizing a healthy individual).

These outcomes are typically placed in the cells of the confusion matrix, often labeled as **a (TP)**, **b (FP)**, **c (FN)**, and **d (TN)**.

Several statistical measures are derived from these values

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- **Specificity** (also known as the **True Negative Rate**, TNR) measures the proportion of actual negatives correctly identified. It is calculated as:
  Sensitivity (also referred to as **Recall** or the **True Positive Rate**, TPR) reflects the proportion of actualpositives correctly identified. It is calculated as:

$$\text{Sensitivity} = \frac{TP}{TP + FN} = \frac{a}{a + c}$$

- **Precision** (also known as the **Positive Predictive Value**, PPV) indicates how many of the predicted positives are actually positive. It is calculated as:

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{a}{a + b}$$

- **F1-Score** provides a balance between precision and recall, serving as their harmonic mean. It ranges from 0 (worst) to 1 (best) and is especially useful when the class distribution is imbalanced. It is given by:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

These evaluation metrics, as discussed by Powers et al. (2011), offer a comprehensive understanding of a model's classification ability and are crucial for validating its real-world performance.

3.4 Schematic layout of suggested approach

This study's findings include a feature extraction method based on an integrated wavelet transform approach. The brain image datasets used for this research were obtained from the publicly accessible repository maintained by (http://www.med.harvard.edu/AANLIB) Harvard University. This resource provides a wide range of brain images, including scans of individuals with various neurological disorders as well as normal brain scans. All images are available in GIF format, grayscale, and standardized to a resolution of 256×256 pixels.

The primary goal of this feature extraction process is to enable the automated classification of brain-related disorders by feeding relevant features into a robust and organized classification model. While there are various existing methods for extracting features from brain images, this work introduces an effective and structured approach utilizing an Integrated Discrete Wavelet Transform (IDWT). Figure 1 shows the system architecture for this approach..

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The methodology begins by collecting a set of transaxial brain images from the aforementioned dataset. It is important to note that brain MRI images can be acquired in multiple anatomical planes: sagittal, coronal, and transaxial. For the scope of this study, only transaxial plane images are considered.

Once the images are collected, the suggested IDWT technique is used to carry out the feature extraction process. It is commonly accepted that one of the best methods for feature extraction is the Discrete Wavelet Transform (DWT). from two-dimensional image data. At the heart of DWT lies the mother wavelet, a function used to analyze the image at various scales and resolutions.

A range of wavelet functions can be employed for this purpose, including Daubechies, Haar, Morlet, Coiflet, and Bi-orthogonal wavelets (such as Bi-orthogonal 1.x). Each wavelet has unique characteristics suitable for different types of image features. The effectiveness of these functions for image processing tasks has been explored in prior works, such as those by Lori Mann Bruce et al. (2002), S. Kother Mohideen et al. (2008), Dipalee Gupta et al. (2015), and Chin-Chin Lai et al. (2010).

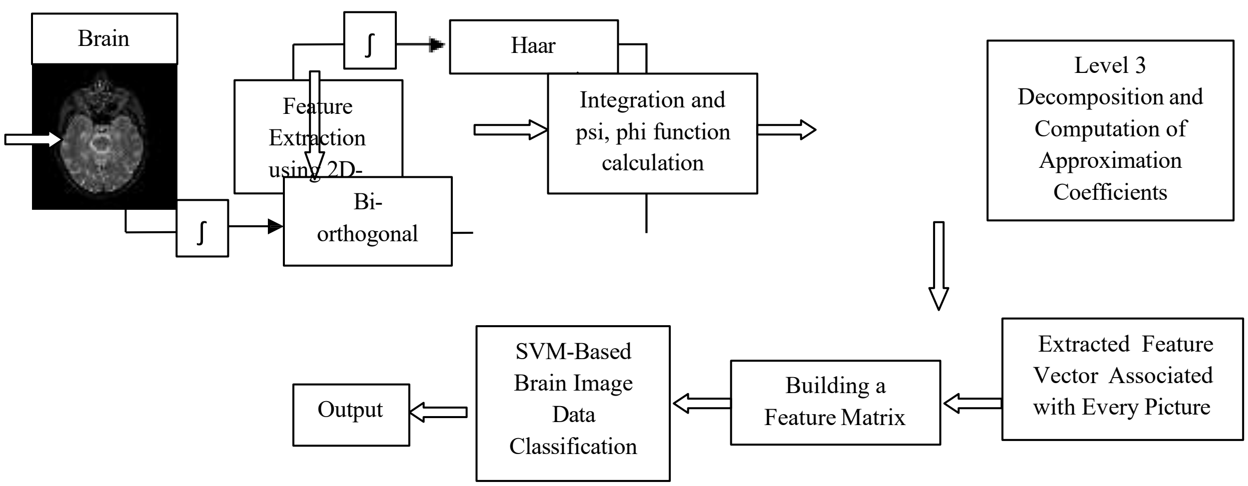

Figure 1. Diagram illustrating the structure of the IDWT is a suggested model for brain imaging feature extraction and categorization.

In this work, we present a method for extracting features from brain pictures using the Integrated Discrete Wavelet Transform (IDWT). The Bi-orthogonal 1.3 wavelet's benefits and the Haar wavelet are combined in this technique. After extracting features using both wavelet functions, the combined after that, a classifier model is fed the feature matrix, specifically a linear kernel Support Vector Machines (SVM) are used to classify various brain diseases. The experimental findings, which are described in the section that follows, show that the suggested IDWT method works better than the use

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of individual wavelet functions. Additionally, we compare the performance of the SVM classifier against other classification methods, including Multi-Layer Perceptron Neural Network (MLPNN), Gaussian Naive Bayes (NB), and Logistic Regression, to assess its effectiveness in brain disorder classification.

4. Results

Wavelet transform is a highly effective method for extracting features from images and analyzing non-stationary signals. Among the various techniques, the Discrete Wavelet Transform (DWT) is widely recognized for its efficiency in image decomposition and feature extraction. The primary one benefit of DWT is its capacity for signal analysis. at several resolution scales, which makes it very helpful for in-depth image analysis.

In this study, we have utilized two commonly used wavelet functions: the orthogonal Haar wavelet and the wavelet of bi-orthogonal 1.3. Equation (7) provides the definition of the mother wavelet function for Haar.

$$\psi(x) = \begin{cases} 1 & 0 \leq x < 1/2 \\ -1 & 1/2 \leq x < 1 \\ 0 & Otherwise \end{cases} \tag{7}$$

The definition of the scaling function can be found in (8).

$$\phi(x) = \begin{cases} 1 & 0 \leq x < 1 \\ 0 & Otherwise \end{cases} \tag{8}$$

The Bi-orthogonal wavelet is an additional wavelet function utilized in this work, where the wavelet functions must remain invertible but need not be orthogonal. Two scaling functions are used in this method (ϕ(x)) are utilized, as expressed in equations (9) and (10), each linked with corresponding wavelet functions (ψ(x)), as detailed in equations (11) and (12).

$$\phi(x) = 2\sum_{-\infty}^{\infty} h(n)\phi(2x-n) \tag{9}$$

$$\tilde{\phi}(x) = 2\sum_{-\infty}^{\infty} \tilde{h}(n)\tilde{\phi}(2x-n) \tag{10}$$

$$\psi(x) = 2\sum_{n=-\infty}^{\infty} g(n)\phi(2x-n) \tag{11}$$

$$\tilde{\psi}(x) = 2\sum_{n=-\infty}^{\infty} \tilde{g}(n)\tilde{\phi}(2x-n) \tag{12}$$

The bi-orthogonal wavelet's ability to produce different multi-resolution analyses is a significant advantage.

In this study, we do not limit ourselves to using standard wavelet functions alone; instead, we have developed The two wavelet functions are combined in an integrated version. The rectangular integra

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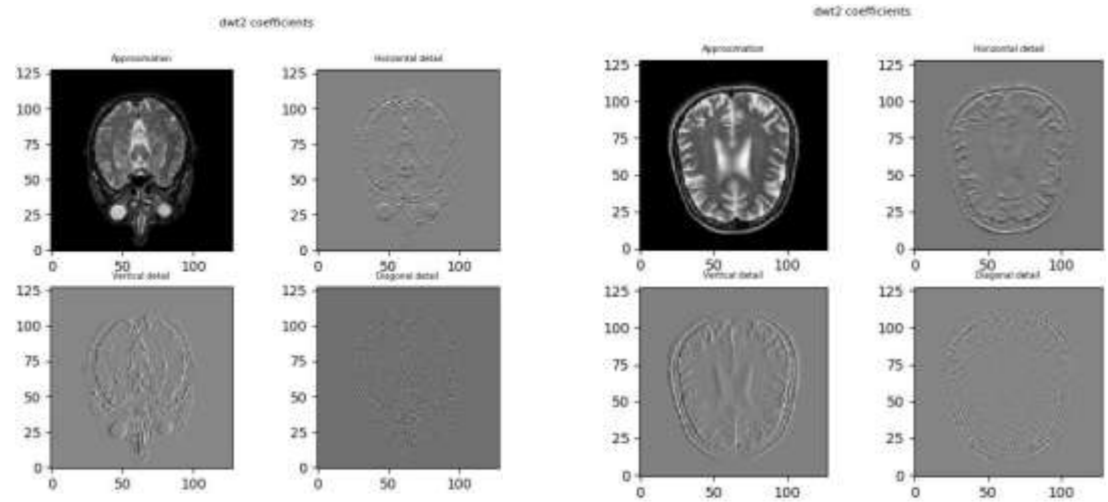
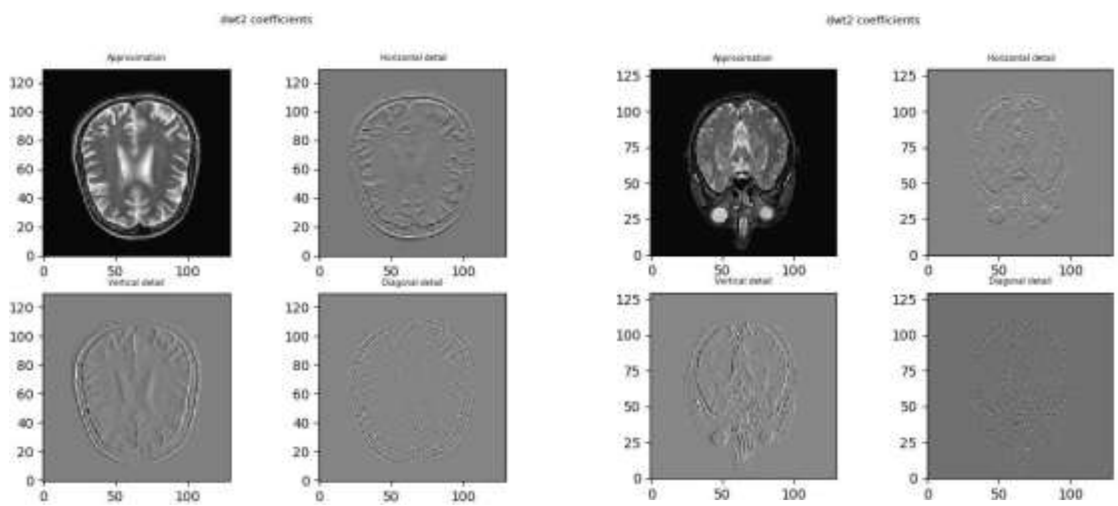
Only one integral wavelet function is calculated because Haar is an orthogonal wavelet. Since bi-orthogonal wavelets are not orthogonal, for reconstruction and decomposition, two integral wavelet functions are computed. An In Figure 2, the integrated Haar wavelet is used to deconstruct the axial plane images of a normal brain and an Alzheimer's brain. The breakdown of the identical images using the integrated Bi-orthogonal 1.3 wavelet function is also shown in Figure 3. Up to level 3, both decompositions are performed. Approximation coefficients, as well as horizontal, vertical, and diagonal detail coefficients, make up each decomposition level.



(A) (B)

Figure 2. DWT feature extraction from the Integrated Haar wavelet function in a normal brain image (A) and an Alzheimer's brain image (B).



(A) (B)

Figure 3. DWT feature extraction using wavelet functions with integrated bi-orthogonal 1.3 from two brain images: one of a normal brain (A) and the other of an Alzheimer's brain (B).

4.1 Algorithm or pseudo code for creation of datasets

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Input: Let L represent the total number of collected 256 x 256 brain images.

Output: A feature matrix made from images

Step 1: Take IMG_k, utilizing IDWT to decompose the image for k=1 to L

Step 2: Set up $C_k = 32 \times 32$ for each image's feature vector storage

Step 3: Determine the Haar wavelet function's integration $Wavelet_1 = intergrate\_Wavelet('Haar')$

Step 4: Determine the Bi-orthogonal 1.3 wavelet function's integration $Wavelet_2 = intergrate\_Wavelet('Bior1.3')$

Step 5: Find 1st , 2nd and 3rd level of coefficients using IDWT,

$$ll3_h, (lh3_h, hl3_h, hh3_h) = paywt.wavelet\ (Wavelet_1)$$

$$ll3_b, (lh3_b, hl3_b, hh3_b) = paywt.wavelet\ (Wavelet_2)$$

Step 6: for i between 1 and 32

Step 7: for j between 1 and 32

Step 8: $C_K = ll3_h + ll3_b$

Step 9: $IMG_k = C_k$

5. Discussion

To assess the effectiveness of the proposed model, a series of experimental evaluations were conducted. These experiments were implemented using Python 2.7, incorporating essential libraries such as NumPy, SciPy, Matplotlib, and Scikit-learn. The testing environment consisted of a personal computer equipped with a running Ubuntu with a 4 GB of RAM and an Intel Core i7 processor running at 3.40 GHz.

The classifier performance was measured using standard evaluation metrics, including accuracy, precision, recall, and F1-score. To ensure reliability and reduce overfitting, each classification model was tested using 5-fold cross-validation.

Table 1. Comparative performance of various classifiers in diagnosing brain disorders utilizing characteristics taken from scans of the brain.

Classification Techniques	Accuracy	Specificity	Sensitivity	F1-Score
MLPNN	0.85 ±0.32	0.85±0.32	0.90±0.30	0.87±0.31
Gaussian NB	0.80±0.24	0.80±0.24	1.00±0.00	0.87±0.16
Logistic Regression	0.95±0.15	0.90±0.30	0.90±0.30	0.90±0.30
SVM with Linear Kernel	0.95±0.15	0.90±0.30	0.90±0.30	0.90±0.30
SVM with Polynomial Kernel	**1.00 ±0.00**	**1.00 ±0.00**	**1.00 ±0.00**	**1.00 ±0.00**

Table 2. Configuration of parameters for classifiers.

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Classification Techniques	Parameters
MLPNN	Activation Function – Sigmoid, Learning Rate = 0.7 Momentum Coefficient = 0.8, Input Bias – Yes
Gaussian NB	Prior probabilities – Random, Theta – mean of each feature per class Sigma – Variance of each feature per class
Logistic Regression	Inverse of regularization strength (C) – 1.0 Intercept scaling -1, Maximum iteration – 100, Tolerance – 1e-4
SVM with Linear Kernel	Kernel Type – Linear, Penalty Factor = 1.0
SVM with Polynomial Kernel	Kernel Type – Polynomial, Degree – 3, Penalty Factor = 1.0

Table 3. Performance comparison between the suggested approach and other tried-and-true methods.

Author	Techniques	Accuracy
Sandeep Chaplot *et al*. (2006)	DWT, SVM (Polynomial)	0.9715
	DWT, SVM (RBF)	0.9733
S. Das *et al*. (2013)	RT, PCA, LS-SVM	1.0000
M. Saritha *et al*. (2013)	DWT, WE, SWP, PNN	0.9988
Y. Zhang *et al*. (2010)	DWT, PCA, FNN, ACPSO	0.9875
El-Dahshan *et al*. (2014)	FPCNN, DWT, PCA, FPANN	0.9888
S. Wang *et al*. (2015)	SWT, PCA, IABAP-FNN	0.9944
	SWT, PCA, ABC-SPSO-FNN	0..9975
El-Dahshan *et al*. (2010)	DWT, PCA, FPANN	0.9698
	DWT, PCA, *k*-NN	0.9754
Proposed Method (IDWT)	**IDWT, SVM (Polynomial)**	**1.0000**

Below is a summary of the main conclusions drawn from the experiments and validation procedures that were carried out:

(a) For each validation round, distinct sets of training and testing samples were used. The average and standard deviation values for performance metrics—accuracy, precision, recall, and F1-score—were calculated across all validation runs and are presented in Table 1.

(b) Based on the data in Table 1, it is evident that the Support Vector Machine (SVM) using a polynomial kernel demonstrates superior performance when compared to the other methods. Although the linear kernel SVM and logistic regression models show equal accuracy, both outperform the Gaussian Naive Bayes (NB) and Multi-Layer Perceptron Neural Network (MLPNN) classifiers.

(c) In this study, SVM was chosen as the primary algorithm for classifying brain disorder images. It is widely recognized for its ability to handle classification tasks in multi-dimensional feature spaces effectively. SVM operates by projecting data into a higher-dimensional space, followed by the use of an ideal hyperplane to separate it. The kernel function used significantly influences the classifier's performance. Among the commonly used kernels—linear, polynomial, and radial basis function (RBF)—this study focuses on the linear and

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(d) polynomial kernels.

(e) The dataset created from the brain images, using the described feature extraction methods, was used as input for the SVM classifier. To benchmark its performance, we compared SVM with other machine learning models, including MLPNN, Naive Bayes, and Logistic Regression. Detailed parameters for each of these models, including both SVM variants, are outlined in Table 2.

(f) Furthermore, the proposed Integrated Discrete Wavelet Transform (IDWT) feature extraction approach was evaluated against several existing methodologies identified during the literature review. According to the results shown in Table 3, the proposed IDWT combined with an SVM using a polynomial kernel achieved the highest accuracy of 100%, outperforming all previously established techniques.

6. Conclusion and Future Work

This study presents a novel Integrated Discrete Wavelet Transform (IDWT) approach that combines Haar and Bi-orthogonal's advantages 1.3 wavelet functions for the creation of a computer-assisted system for diagnosing illnesses of the human brain. To improve the data's representational quality, features are separately retrieved using both wavelet types and then combined into a single feature vector. Several machine learning techniques were used to do the classification process, such as Gaussian Naive Bayes (NB), Logistic Regression, Support Vector Machines (SVM) using both linear and polynomial kernels, and a Multi-Layer Perceptron Neural Network (MLPNN). Among these, SVM with a polynomial kernel achieved the highest classification accuracy, reaching 100%. However, classification accuracy alone does not fully reflect the reliability or robustness of the model. To provide a more comprehensive evaluation, the proposed IDWT model was also assessed using additional performance metrics such as precision, recall, and F1-score. Furthermore, its performance was benchmarked against several existing techniques discussed in the literature review. Looking ahead, the proposed image processing framework holds significant potential to enhance diagnostic interpretation for medical professionals. It may support researchers and clinicians by improving visual analysis capabilities and contributing to more accurate and efficient medical decision-making.

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