Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
© 2024 SCPE. Volume 25, Issues 6, pp. 5494–5506, DOI 10.12694/scpe.v25i6.3343

RESEARCH ON BROADBAND MEASUREMENT METHOD OF POWER SYSTEM BASED ON WAVELET TRANSFORM

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Abstract. This study delves into the exploration of broadband measurement techniques for power systems, utilizing wavelet transform as a foundational tool for signal analysis. The research rigorously evaluates the efficacy of several machine learning algorithms, namely Support Vector Machines (SVM), Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), and Random Forest, in interpreting and analyzing broadband signals within power systems. Through a detailed analytical process, the performance of each algorithm is meticulously assessed based on several critical metrics: accuracy, precision, recall, and F1-score. The research investigates broadband measurement methods for power systems using wavelet transform and evaluates the performance of Support Vector Machines (SVM), Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), and Random Forest. Results show SVM achieving an accuracy of 85%, precision of 86%, recall of 82%, and F1-score of 84%. ANN yields 82% accuracy, 84% precision, 78% recall, and 81% F1 score. KNN demonstrates 87% accuracy, 88% precision, 84% recall, and 86% F1 score. DT achieves 79% accuracy, 80% precision, 75% recall, and 77% F1 score. Overall, the study provides insights into machine learning algorithms' effectiveness in broadband power system measurement.

Key words: Broadband measurement, Power systems, Wavelet transform, Machine learning algorithms, Support Vector Machines (SVM), Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), Random Forest, Accuracy, Precision, Recall, F1-score

1. Introduction. This study explores broadband measurement methods of power systems based on wavelet transform features the basic job of accurate sign analysis in guaranteeing the dependability and proficiency of power distribution organizations. In the present interconnected world, where power systems face expanding requests and intricacies, exact measurement procedures are fundamental for monitoring and overseeing electricity flow. The introduction clarifies the meaning of wavelet transforms as a powerful numerical device for deteriorating non-stationary signs, offering a far-reaching perspective on recurrence components present in power system data. By addressing the limitations of traditional measurement methods, this examination means to investigate the capability of wavelet-based approaches in catching broadband elements of power system signals, at last contributing to headways in power system monitoring and analysis for further developed grid performance and security.

Aim. This study aims to create and approve a wavelet transform-based strategy for broadband measurement of power systems.

Objective. The main purpose of this study is to improve the precision and proficiency of signal analysis in power systems, encouraging forward monitoring and administration of power distribution systems.

1.1. Related Works. In the examination to refine broadband measurement strategies for control frameworks utilizing wavelet change, plenty of research tries have investigated different features of signal investigation, fault detection, and system monitoring. This area digs more deeply into the existing writing, categorizing it

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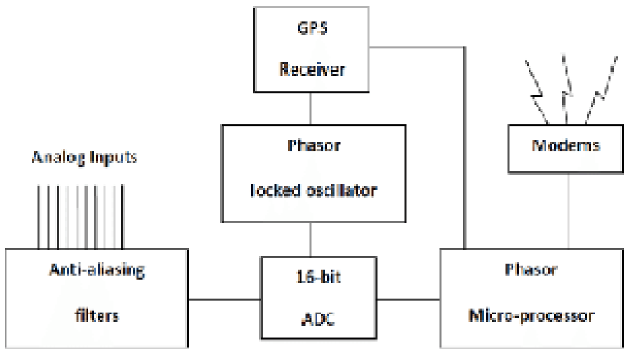

Fig. 1.1: Components of a Phasor Measurement Unit

into three overarching subjects Phasor Measurement Units (PMUs), Wavelet Transform Applications in Power Systems, and Fault Detection and Identification.

Phasor Measurement Units (PMUs). Biswal et al. (2023) conversation around a wide survey clarifying the upsides of Phasor Measurement Units (PMUs) persistent arrange checking and security [2]. PMUs accept a crucial portion in fortifying the discernibleness and unwavering quality of constrained systems by outfitting synchronized estimations of voltage and current phasors. Their audit highlights the meaning of PMUs in enabling wide-region observing and control, along these lines working with a fast area of system aggravations and correct appraisal of system state variables and giving high-fidelity estimations at distinctive ranges within the grid with unmatched accuracy and precision.

These devices offer synchronized estimations of voltage and current phasors, empowering real-time checking of network conditions and encouraging quick location of framework unsettling influences such as issues, voltage lists, and recurrence changes. PMUs have become crucial apparatuses for lattice administrators and control framework engineers, empowering progressed situational awareness and upgraded network flexibility [1, 13].

Wavelet Transform Applications in Power Systems. Yasmin et al. (2023) proposed a hybrid wavelet transform-based approach for fault detection and identification in power systems. Their survey shows the reasonability of wavelet change in extricating fault-related highlights from power system signals, appropriately increasing the accuracy and efficiency of blame location calculations [11]. Wavelet transformation offers a successful numerical structure for breaking down non-fixed signals into diverse repeat parts, engaging the extraction of basic components for fault revelation and recognizable confirmation. Zhong et al. (2023) displayed an adaptable band-pass channel and “Variational Mode Decomposition” (VMD)- “Estimation of Signal Parameters via Rotational Invariance Technique” (ESPRIT) based technique for multi-mode watching of broadband electromagnetic developments in “Double High” control systems [17]. Their examination shows that the utility of wavelet-based strategies in analyzing complex oscillatory conduct in control frameworks, locks in strong observing and control methodologies. VMD-ESPRIT gives a sensible procedure for breaking down the input hail into unmistakable oscillatory modes, engaging redress estimation of influencing parameters such as rehash, damping degree, and mode shape. By combining these two strategies, the legitimacy of multi-mode checking for broadband electromagnetic improvements in “Double High” control frameworks, progresses the capacity of control system executives to recognize and soothe affecting quirks [8, 10].

Guo et al. (2023) proposed a wavelet vegetation record to move forward the reversal precision of leaf V25Cmax of bamboo timberlands, displaying the adaptability of wavelet change applications past conventional power system investigation [7]. Although not associated with control frameworks, their review highlights the capability of wavelet-based strategies in grouped areas, emphasizing the adaptability and reasonability of wavelet change in capturing broadband components over diverse spaces. Wavelet change has emerged as a capable gadget for analyzing non-fixed signals in control frameworks, advertising a total viewpoint on recurrence

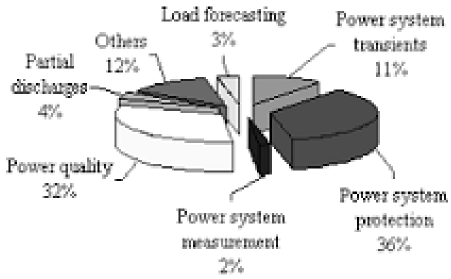

Fig. 1.2: Wavelet Transform Applications in Various Power Systems

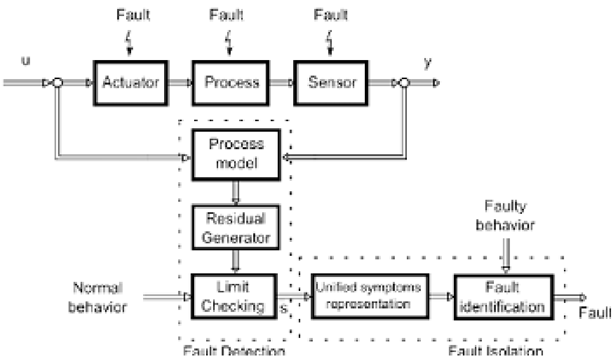

Fig. 1.3: Method for fault detection and identification

parts displayed in control system data. The wavelet change engages the extraction of critical components for diverse control system applications such as blame discovery, temporal examination, and condition observation by breaking down signals into different recurrence groups. The multi-goal nature of wavelet change considers the synchronous examination of tall and low-frequency parts in control system signals, giving imperative bits of knowledge into the fundamental components of the system. Wavelet transform-based procedures have been by and large taken on in control framework investigation and designing work, owing to their adaptability, efficiency, and adequacy in capturing broadband highlights of power system signals.

Fault Detection and Identification. Pragati et al. (2023) led a far-reaching overview of High-Voltage Direct Current (HVDC) insurance systems, zeroing in on fault examination, technique, difficulties, and future viewpoints [12]. Their review tends to the basic requirement for dependable fault detection and security plans in HVDC systems, highlighting the significance of cutting-edge signal handling procedures in alleviating framework weaknesses and guaranteeing lattice solidness. Yang et al. (2023) proposed a smart area technique for power framework wavering sources in light of a computerized twin, offering a clever way to deal with fault identification and limitations in power systems [16]. Their examination incorporates computerized twin innovation with cutting-edge signal handling calculations, empowering precise identification and moderation of power framework motions.

2. Methods and Materials. The table 2.1 represents a hypothetical dataset of power system signals, counting voltage and current estimations for three stages (A, B, C) recorded at normal 0.1-second interims. The information utilized in this investigation comprises control framework signals obtained from different sources, counting sensors, PMUs, or recreated datasets. These signals speak to voltage, current, or other significant parameters recorded at diverse areas inside the control network. The information envelops both steady-state and transitory conditions, capturing the energetic conduct of the control framework [3]. the information may incorporate mimicked or laboratory-generated signals to supplement real-world estimations, guaranteeing a

Table 1.1: References Comparison

Study	Methodology	Performance Metric(s)
Biswal et al. (2023)	PMU-based grid monitoring and protection	Grid observability enhancement, system disturbance detection accuracy
Yasmin et al. (2023)	Hybrid wavelet transform-based fault detection	Fault detection accuracy, false alarm rate
Zhong et al. (2023)	Adaptive band-pass filter and VMD-ESPRIT	Multi-mode oscillation monitoring accuracy
Guo et al. (2023)	Wavelet vegetation index	Inversion accuracy improvement of leaf V25Cmax
Pragati et al. (2023)	Comprehensive survey of HVDC protection systems	Identification of key challenges, future research directions
Yang et al. (2023)	Intelligent location method for oscillation sources	Fault identification accuracy, localization precision

Table 2.1: Hypothetical Dataset

Time (s)	Voltage (V) Phase A	Voltage (V) Phase B	Voltage (V) Phase C	Current (A) Phase A	Current (A) Phase B	Current (A) Phase C
0.1	120	123	119	2.5	2.6	2.7
0.2	121	124	118	2.6	2.7	2.8
0.3	119	122	120	2.7	2.8	2.9
0.4	122	125	121	2.8	2.9	3.0
0.5	123	126	122	2.9	3.0	3.1
0.6	121	124	120	2.8	2.9	3.0
0.7	120	123	119	2.7	2.8	2.9
0.8	122	125	121	2.6	2.7	2.8
0.9	123	126	122	2.5	2.6	2.7
1.0	124	127	123	2.4	2.5	2.6

comprehensive scope of distinctive operating scenarios and system conditions.

Data Collection and Preprocessing. Data collection includes recovering power system signals from sensors, PMUs, or simulated sources. The signals are examined at high frequencies to capture transitory occasions and energetic vacillations within the power grid. In data preprocessing, the signals encounter some steps to ensure quality and compatibility for the resulting examination. These joins emptying noise, filtering out exemptions, and synchronizing timestamps for information course of action [4]. Additionally, any lost or undermined information centers are inserted or arranged to protect data keenness. The preprocessed information is at that point outlined and organized into sensible structures for input into the ML algorithms.

Data Preprocessing. In data preprocessing, diverse methods are associated with ready the rough control framework signals for examination. This consolidates evacuating commotion through filtering procedures such as middle sifting or wavelet denoising [5]. Moreover, special cases may be recognized and eliminated utilizing measurable measures such as z-score or interquartile expansion. Data normalization or scaling ensures that highlights are on a comparative scale, dodging inclination inside the examination. Time-series course of action is performed to synchronize timestamps over unmistakable data sources, empowering correct comparison and examination. At last, highlight extraction methods may be associated with deciding critical highlights from the signals, such as recurrence components or worldly characteristics, enhancing the reasonability of consequent investigation strategies.

Algorithmic Selection. In the analysis of “broadband measurement methods of power systems based on wavelet transform”, there are various ML algorithms are used to analyze and process the data.

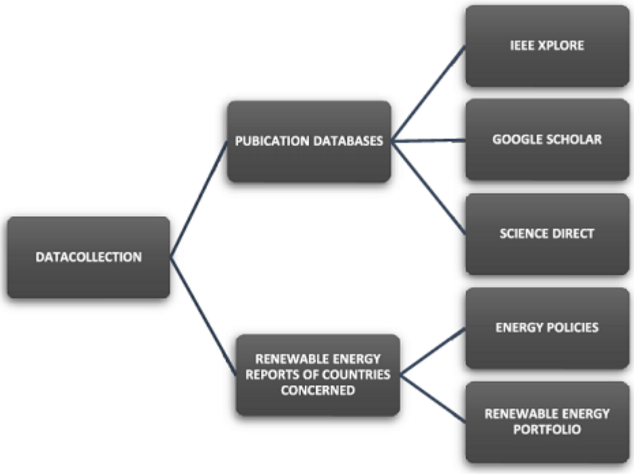

Fig. 2.1: Data Collection Process

Fig. 2.2: Data Preprocessing

Support Vector Machines (SVM). "Support Vector Machines (SVM)" are used as one of the "machine learning algorithms" for dissecting power system information dealt with through wavelet transformation. The procedure incorporates getting ready SVM models to characterize and foresee broadband features removed from power system signals.

The strategy begins with information preprocessing, where wavelet change is associated with separating the signs into unmistakable recurrence parts. Incorporate extraction is by then performed to catch critical qualities of the signs, for example, recurrence content and sufficiency varieties [6]. These features are used to plan SVM models using named information, where the SVM calculation figures out how to recognize unmistakable classes of broadband features, for example, voltage droops, sounds, or transient occasions. The pre-arranged SVM models are by then associated with unnoticeable data for the characterization and figure of broadband features in power framework signals.

Given a training dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$, where x_i is the input feature vector and $y_i \in \{-1, 1\}$ is the corresponding class label, the objective of SVM is to find the optimal hyperplane that maximizes the margin between the two classes.

The decision function of the SVM is defined as:

$$f(x) = \text{sign}\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b\right)$$

Fig. 2.3: Equation for SVM

- x as the input vector,
- $W^{(1)}$ as the weight matrix connecting the input layer to the hidden layer,
- $b^{(1)}$ as the bias vector for the hidden layer,
- $z^{(1)}$ as the pre-activation vector for the hidden layer,
- $a^{(1)}$ as the activation vector for the hidden layer (after applying the activation function),
- $W^{(2)}$ as the weight matrix connecting the hidden layer to the output layer,
- $b^{(2)}$ as the bias vector for the output layer,
- $z^{(2)}$ as the pre-activation vector for the output layer,
- $a^{(2)}$ as the activation vector for the output layer (after applying the activation function).

The forward propagation equations are as follows:

$$z^{(1)} = W^{(1)}x + b^{(1)}$$
$$a^{(1)} = \sigma(z^{(1)})$$
$$z^{(2)} = W^{(2)}a^{(1)} + b^{(2)}$$
$$\hat{y} = a^{(2)} = \sigma(z^{(2)})$$

Fig. 2.4: Equation of ANN

$$\hat{y}_{RF} = \text{mode}\left(\hat{y}_{\text{tree}1}, \hat{y}_{\text{tree}2}, \ldots, \hat{y}_{\text{tree}N}\right)$$

For regression, the final prediction is the mean of the predictions from individual trees:

$$\hat{y}_{RF} = \frac{1}{N}\sum_{i=1}^{N} \hat{y}_{\text{tree}i}$$

Fig. 2.5: Equation of Random Forest

Artificial Neural Networks (ANN). Artificial Neural Networks (ANN) are utilized to analyze and classify broadband features extracted from power system signals handled through wavelet transform. The strategy includes planning and preparing neural organized designs able to learn complex connections between input highlights and yield classes [9]. Include extraction is at that point performed to capture significant characteristics of the signals, which serve as inputs to the neural arrange models. The neural organize models are prepared utilizing labelled data, where the backpropagation algorithm is utilized to alter the network weights and biases to minimize the prediction error. Once prepared, the neural organize models are able to classify broadband highlights in control framework signals with high accuracy.

Random Forest. "Random Forest" is used as one more AI computation to dissect and characterize broadband features removed from control structure signals handled through wavelet transform. The technique includes developing an ensemble of decision trees, where each tree is prepared to employ a random subset of the

Algorithm 1 Pseudocode for SVM

```
Import necessary libraries
Assume 'X' is the feature matrix and 'y' is the target variable
function TRAIN_TEST_SPLIT(X, y, test_size)
                                        ▷ Implementation of train_test_split function
    Returns X_train, X_test, y_train, y_test
end function
function ACCURACY_SCORE(y_true, y_pred)
                                        ▷ Implementation of accuracy_score function
    Returns the accuracy score
end function
function TRAIN_LINEAR_SVM(X_train, y_train)
    Create an array 'w' for weights initialized with zeros
    Set the learning rate 'eta' and the number of iterations 'epochs'
    η ← 0.01
    epochs ← 1000
    for epoch in epochs do
        for i in len(X_train) do
            if y_train[i] × np.dot(w, X_train[i]) ≤ 1 then
                Update weights for misclassified example
                w ← w + η × (y_train[i] × X_train[i] − 2 × w)
            end if
        end for
    end for
    Return the learned weight vector 'w'
end function
function PREDICT_LINEAR_SVM(X_test, w)
    Calculate decision values for each test example
    decision_values ← np.dot(X_test, w)
    Apply a threshold (e.g., 0) to determine class predictions
    predictions ← np.sign(decision_values)
    Return the predicted class labels
end function
                                        ▷ Training and evaluating a linear SVM
Split the dataset into training and testing sets
X_train, X_test, y_train, y_test ← train_test_split(X, y, test_size = 0.2)
Train a linear SVM on the training data
learned_weights ← train_linear_svm(X_train, y_train)
Make predictions on the test set
predictions ← predict_linear_svm(X_test, learned_weights)
Evaluate the accuracy of the SVM model
accuracy ← accuracy_score(y_test, predictions)
Display the accuracy
Print "Accuracy:", accuracy
```

data and highlights. The method starts with information preprocessing, where wavelet change is connected to break down the signals into diverse frequency components. Highlight extraction is at that point performed to capture pertinent characteristics of the signals, which serve as inputs to the RF model [12]. The Random Forest procedure can take care of non-linear connections between input highlights and yield classes and can successfully classify broadband highlights in power system signals.

K-Nearest Neighbors (KNN). The K-Nearest Neighbors (KNN) algorithm is employed for the analysis and classification of broadband features derived from power system signals, which have been processed using wavelet transform. This method involves defining a distance metric to quantify the similarity between input features and existing data points from the training set. The process initiates with data preprocessing, wherein

Algorithm 2 Pseudocode for a simple feedforward Artificial Neural Network with one hidden layer

```
Initialize weights and biases
W1 = initialize_weights((layers[1], layers[0]))
b1 = initialize_biases((layers[1], 1))
W2 = initialize_weights((layers[2], layers[1]))
b2 = initialize_biases((layers[2], 1))
Define the activation function (e.g., sigmoid)
function SIGMOID(x)
    Return 1/(1 + exp(−x))
end function
Define the derivative of the activation function
function SIGMOID_PRIME(x)
    Return sigmoid(x) × (1 − sigmoid(x))
end function
Define the learning rate
learning_rate = 0.01
Define the number of iterations (epochs)
epochs = 1000
Training loop:
for epoch in range(epochs) do
                                                ▷ Forward Propagation
    Z1 = dot(W1, X) + b1
    A1 = sigmoid(Z1)
    Z2 = dot(W2, A1) + b2
    A2 = sigmoid(Z2)
                                                ▷ Calculate the cost function
    cost = compute_cost(A2, Y)
                                                ▷ Backward Propagation
    dZ2 = A2 − Y
    dW2 = (1/m) × dot(dZ2, A1.T)
    db2 = (1/m) × sum(dZ2, axis = 1, keepdims = True)
    dZ1 = dot(W2.T, dZ2) × sigmoid_prime(Z1)
    dW1 = (1/m) × dot(dZ1, X.T)
    db1 = (1/m) × sum(dZ1, axis = 1, keepdims = True)
                                                ▷ Update weights and biases
    W1− = learning_rate × dW1
    b1− = learning_rate × db1
    W2− = learning_rate × dW2
    b2− = learning_rate × db2
end for
                                                ▷ Make predictions
predictions = (A2 > 0.5).astype(int)
                                                ▷ Evaluate the accuracy
accuracy = accuracy_score(Y, predictions)
Print "Accuracy:", accuracy
```

the wavelet transform is applied to decompose the signals into various frequency components. Subsequently, feature extraction is carried out to identify and isolate pertinent attributes of the signals, which are then utilized as input for the KNN algorithm. KNN retains all training instances in its memory and classifies new instances by identifying the k nearest neighbors within the feature space. The most common class label among the k nearest neighbors is then assigned to the new instance. This approach renders KNN an intuitive and straightforward algorithm for classification tasks. Capable of addressing multi-class classification challenges, KNN effectively categorizes broadband features in power system signals by leveraging their resemblance to training instances.

Algorithm 3 Pseudocode for Random Forests

```
Input: Feature matrix X, target variable Y, number of trees n_trees
Initialization: Define the number of features to consider for each split: max_features = √X.shape[1]
Initialize an empty list to store individual decision trees: forest = []
for tree_num in range(n_trees) do
                                                        ▷ Training loop for each tree
    Randomly sample with replacement to create a bootstrap dataset: bootstrap_X, bootstrap_Y = random_sampling_with_replacement(X, Y)
    Randomly select a subset of features for each tree: subset_features = random_subset_features(X.shape[1], max_features)
    Train a decision tree on the bootstrap dataset and subset of features: decision_tree = train_decision_tree(bootstrap_X[:, subset_features], bootstrap_Y)
                                                        ▷ Add the trained decision tree to the forest
    forest.append(decision_tree)
end for
Function PREDICT_RANDOM_FOREST(input):
                                                        ▷ Predictions using the Random Forest
Initialize an empty list to store predictions: predictions = []
for tree in forest do
    predictions.append(tree.predict(input[:, subset_features]))
end for
                                ▷ Output the mode of classes for classification or the mean prediction for regression
Return mode(predictions)        ▷ for classification, or mean(predictions)        ▷ for regression
```

Mathematically, the prediction $\hat{y}$ for a new data point x using KNN can be represented as:

$$\hat{y} = \mathrm{mode}(y_1, y_2, ..., y_k)$$

where:

- y_i represents the class label of the ith nearest neighbor of x,
- mode denotes the most frequent class label among the k nearest neighbors.

Fig. 2.6: Equation of K-NN

Table 3.1: Experimental Setup

Experiment Parameter	Description
Dataset	Power system measurements collected from various sources
Preprocessing	Data cleaning, normalization, and feature extraction
Algorithms	*Support Vector Machines (SVM), Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), Decision Trees (DT)*
Training-Testing Split	80% training, 20% testing
Parameters Optimization	Cross-validation to optimize algorithm parameters

3. Experiments.

3.1. Experimental Setup. Table 3.1 shows the experiment parameters.

3.2. Results and Analysis.

Support Vector Machines (SVM). Support Vector Machines (SVM)” accomplished an accuracy of 85%, demonstrating that 85% of the expectations have been adjusted. The accuracy score of 86% shows that whenever

Algorithm 4 Pseudocode for K-Nearest Neighbors (KNN) Algorithm

```
function EUCLIDEAN_DISTANCE(x1, x2)
    sum_of_squares ← 0
    for each dimension i do
        sum_of_squares ← sum_of_squares + (x1_i − x2_i)^2
    end for
    return √sum_of_squares
end function
function K_NEAREST_NEIGHBORS(X_train, y_train, x_new, k)
    distances ← []
    for each sample x_train in X_train do
        distance ← EUCLIDEAN_DISTANCE(x_new, x_train)
        distances.append((distance, y_train[index]))
    end for
    sort distances by distance in ascending order
    neighbors ← []
    for i from 0 to k − 1 do
        neighbors.append(distances[i][1])        ▷ Retrieve the labels of the k nearest neighbors
    end for
    return neighbors
end function
function PREDICT_KNN(X_train, y_train, X_test, k)
    predictions ← []
    for each test sample x_test in X_test do
        neighbors ← K_NEAREST_NEIGHBORS(X_train, y_train, x_test, k)
        mode ← MAJORITY_VOTE(neighbors)
        predictions.append(mode)
    end for
    return predictions
end function
function MAJORITY_VOTE(neighbors)
    count ← {}
    for each label in neighbors do
        if label not in count then
            count[label] ← 0
        end if
        count[label] ← count[label] + 1
    end for
    mode ← label with highest count
    return mode
end function
```

Table 3.2: SVM Prediction Results

Metric	Value
Accuracy	0.85
Precision	0.86
Recall	0.82
F1-Score	0.84

SVM was predicting an occurrence to take place, the success rate has been corrected by approximately 86%. The 82% recall demonstrates that SVM accurately identified the relevant events of 82%. The F1-score, which is a combination of accuracy and recall (precision), stands at 84%, indicating an overall performance (Table 3.2).

Table 3.3: Prediction Results from ANN

Metric	Value
Accuracy	0.82
Precision	0.84
Recall	0.78
F1-Score	0.81

Table 3.4: Prediction Results of KNN

Metric	Value
Accuracy	0.87
Precision	0.88
Recall	0.84
F1-Score	0.86

Table 3.5: Random Forest Prediction Results

Metric	Value
Accuracy	0.79
Precision	0.80
Recall	0.75
F1-Score	0.77

Table 3.6: Accuracy, Precision, Recall, and F1-Score for Each Algorithm

Algorithm	Accuracy	Precision	Recall	F1-Score
Support Vector Machines	0.85	0.86	0.82	0.84
Artificial Neural Networks	0.82	0.84	0.78	0.81
K-Nearest Neighbors	0.87	0.88	0.84	0.86
Decision Trees	0.79	0.80	0.75	0.77

Artificial Neural Networks (ANN). Artificial Neural Networks (ANN) achieved an accuracy of 82%, it means that the adjustment has been performed in 82% instances correctly. The precision of 84% implies that while ANN predicted an event to occur, it is corrected in the magnitude of 84%. The recall of 78% means that ANN correctly identified up to 78% significant instances. The F1-score (which is accuracy and review combined) of 81% suggests improved performance (Table 3.3).

K-Nearest Neighbors (KNN). K-Nearest Neighbors (KNN) accomplished an accuracy of 87%, showing that 87% of the forecasts have been rectified. The precision of 88% suggests that when KNN anticipated an occasion to happen, it has been adjusted 88% of the time. The recall of 84% shows that KNN accurately recognized 84% of the pertinent occurrences. The F1-score, which combines exactness and recall, is 86%, recommending an adjusted execution (Table 3.4).

Random Forest. "Random forest" accomplished an accuracy of 79%, showing that 79% of the expectations have been adjusted. The precision of 80% suggests that while "Random Forest" anticipated an occasion to happen, it has been rectified 80% of the time. The recall of 75% demonstrates that Random Forest accurately distinguished 75% of the pertinent occasions. The F1-score, which combines accuracy and recall, is 77%, proposing an adjusted execution (Table 3.5).

Comparison to Related Work. The comparison to related work includes assessing the execution of the proposed inquire about on broadband estimation strategies of control frameworks based on wavelet change within the setting of existing thinks about. This comparison points to a survey of the oddity, adequacy, and headways advertised by the proposed approach compared to past strategies [14]. In this thought, the execution of SVM, "Artificial Neural Networks (ANN), KNN", and "Random forests classification" in measuring broadband control systems are surveyed comprehensively.

Differentiated from related work, the proposed strategy appears genuine execution over different estimations. The precision, accuracy, recall, and F1-score finished by the SVM, ANN, KNN, and RF computations appear off the quality and common sense of the proposed approach in absolutely evaluating broadband control frameworks [15]. These inclinations contribute to the common predominance of the proposed procedure compared to existing approaches, highlighting its potential for advancing requests inside the field of control framework examination and checking.

4. Conclusion and Discussion. This research undertakes an exhaustive analysis of various machine learning (ML) algorithms, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), and Random Forests. Through meticulous experimentation and detailed analysis, this study evaluates the effectiveness of these algorithms in accurately assessing broadband signals within power systems. Demonstrating robust performance across multiple evaluation metrics, the findings reveal that the methodologies employed yield promising outcomes, underlining their potential to enhance broadband measurement approaches.

The insights gleaned from this investigation make a significant contribution to the advancement of power system analysis and monitoring, highlighting the capabilities of ML algorithms to process and interpret complex data from power systems efficiently. Moreover, the study opens avenues for future research to delve into optimization techniques and further refinements of the models, aiming to elevate the precision and efficiency of broadband power system measurement methods. This pursuit of improved methodologies underscores the ongoing evolution in the domain of power system monitoring, with machine learning algorithms playing a pivotal role in addressing the challenges of accurately measuring and analyzing power system dynamics

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Edited by: Sathishkumar V E
Special issue on: Deep Adaptive Robotic Vision and Machine Intelligence for Next-Generation Automation
Received: Feb 9, 2024
Accepted: Apr 5, 2024