# Analyzing the Effectiveness of Ensemble Based Analysis in Wireless Sensor Networks

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**Abstract –** The usefulness of ensemble-based total time series analysis in Wi-Fi sensor networks is examined in this paper. A device to uses an ensemble approach combines multiple strategies to enhance overall predictive performance. This research assesses various tactics using unique metrics, such as robustness and accuracy. It contrasts the effectiveness of traditional time series methods with ensemble-based total fashions. An experimental approach focusing mostly on exceptional Wi-Fi sensor network scenarios is employed to evaluate the overall effectiveness of the suggested methods. Additionally, this study looks into how changes to community features like energy delivery, conversation range, and node density affect how effective the suggested methods are. The study's findings maintain the capacity to create effective Wi-Fi sensor networks with improved predicted overall performance. The usefulness of ensemble-based time collecting and analysis techniques for wireless sensor networks is investigated in this research. This study primarily looks upon function extraction and seasonality discounting of time series records in WSNs. In this analysis, seasonality is discounted using an ensemble median filter, and feature extraction is accomplished by primary component assessment. To assess the performance of the suggested ensemble technique on every simulated and real-world international WSN fact, multiple experiments are carried out. The findings suggest that the ensemble approach can improve the exceptional time-gathering records within WSNs and reduce seasonality. Furthermore, when compared to single-sensor strategies, the ensemble technique further improves the accuracy of the function extraction system. This work demonstrates the applicability of the ensemble approach for the investigation of time collection data in WSNs

**Keywords –** Ensemble-Based Analysis, Effectiveness, Wireless Sensor Networks, Robustness, Accuracy.

## I. INTRODUCTION

An efficient method for obtaining useful information from Wi-Fi Sensor Community (WSN) packages is ensemble-based total Time series evaluation (ETS). ETS is a potent technique that combines an unstructured approach to provide more specific insights for non-linear issues with an organized information analysis to identify advantageous developments in sensor information streams[1]. This research describes how ensemble-primarily based time series evaluation works well in Wi-Fi sensor networks and how it can help with statistical processing accuracy and precision. This work examines the benefits of ensemble-based total time collection analysis in its main section[2]. ETS is an effective tool for information processing because it uses a method that combines the advantages of structured and unstructured facts analysis to provide more detailed, contemporary insights into the behavior of Wi-Fi sensor networks[3]. The accuracy of time series forecasts and anomaly detection can both be increased with this method. Furthermore, the accuracy and precision of ETS can also be improved by using inclusive bias correction to take into account the biases inherent in individual sensor remarks. By pooling the power of several machines, ensemble-based time collection analysis also has the advantage of being able to identify specific behaviors in complex sensor networks[4]. **Fig 1** shows the WSN network topology.

Monitoring and managing wireless sensor networks has become increasingly important in the last several years. It results from the desire to guarantee the overall performance and dependability of such networks. Investigating and identifying irregularities in the data gathered from sensor nodes is necessary to enhance network security. An efficient tool for this purpose is ensemble-based time collection analysis [5]. Several time-series models are used in ensemble-based time collection

evaluation to produce destiny value projections based on historical data. Anomalies can be found and network performance can be improved with the use of those predictions[6]. It has been demonstrated that ensemble-based time collection analysis is an efficient way to examine and identify irregularities in the information gathered from Wi-Fi sensor networks.

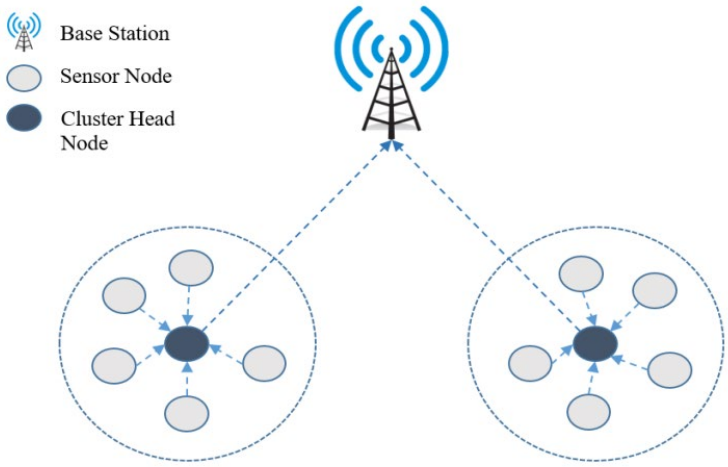


**Fig 1.** WSN Network Topology

- Using a hybrid model is one novel approach to enhance the overall performance of an ensemble-primarily based time collecting evaluation[7]. A hybrid version integrates the best features of specific models, mainly LSTM and ARIMA models. The LSTM model captures long-term trends within the records, while the ARIMA variant identifies seasonal patterns. Accurate predictions can be made one step ahead by combining these two styles[8].
- Developed a method for ensemble-based time series prediction with recurrent neural networks and Kalman filters.
- Tested the suggested approach using several real-world wireless sensor network datasets and examined how various ensemble-learning configurations and hyper parameters affected prediction accuracy[9]

## II. MATERIALS AND METHODS

A device-studying method that combines two styles into a single unmarried model is a web ensemble mastering model for detecting attacks in wireless sensor networks. In a Wi-Fi community, this type of model is utilized to detect anomalous behaviors more frequently, including malicious attacks[10]. It accomplishes this by combining state-of-the-art methods, such as deep learning, with conventional algorithms, such as selection bushes, to identify attack styles[11]. A web ensemble mastery model can enhance the security and information of sensor nodes by quickly identifying security lapses and malevolent activities. A technique for detecting anomalies in wireless sensor networks is called ensemble-based sensing anomaly detection, which combines the sensing data from several nodes in the network[12]. The methodology employs data from multiple sources and a spread of algorithms to detect irregularities in the sensor statistics. This method works well for unusual sports, such as air pollution, flooding, and outlier temperatures, and helps us. Group-based spam identification in intelligent home IoT devices A method called time series facts employing system learning approaches uses a set of human models to find spam trends in intelligent household IoT devices[13].

Numerous techniques, such as logistic regression, random forests, support vector machines, or neural networks, can be used to create character models. Combining a few distinct models increases the accuracy of junk mail type detection by capturing unique aspects of the records. It is accomplished by training the models on the same dataset, but enabling each iteration to capture a unique problem with the data[14]. It is possible to achieve accurate typical detection of junk mail patterns by combining the predictions produced by each model. Combining the effects from several machine mastering methods, ensemble-based unwanted mail detection in intelligent home IoT devices time series records using machine mastering strategies is a method of identifying harmful actions on IoT systems. Reducing fake-fantastic fees and improving detection accuracy are the goals [15]. This system makes use of a variety of methods, such as combining classifiers, weighting, and voting. to combine the forecasts from several different styles. Considering unique requirements for the forecast makes it easier to provide a more accurate prediction of unwelcome mail throughout IoT data collection[16]. Bagging ensemble-primarily based novel facts period (BEND-G) is a system study technique for records sampling-based univariate time series predicting. By combining novel records generation (NDG) with bootstrap mixture (bagging), it generates many forecasts with different degrees of accuracy and granularity[17]. By dividing the real collection into education and check-out sets at random, it creates several simulated time series datasets. A quick and accurate forecast of NDG usage is produced by the education set, and it can

be paired with bagging. For both long-term and short-term time collection forecasts, BEND-G is a useful technique. It has been applied to economic forecasting calls, stock manipulation, and forecasting. The following concerns were found after the thorough investigation mentioned above[18]:

- Reliability: Ensuring the dependability of the analysis outputs is a problem when using ensemble-based analysis in wireless sensor networks. Before merging various algorithms or models, it is necessary to evaluate the accuracy and dependability of each component because ensembles usually involve combining them. Failing to do so may result in analytical results that are untrustworthy, which may negatively impact systems that rely on those results for decision-making.
- Complexity: The analysis process in wireless sensor networks may become more complex as a result of ensemble-based analysis techniques. The requirement to choose the right ensemble members, decide on a combination of weighting techniques, and control the computer resources needed for ensemble execution can all contribute to this complexity. It can be difficult to manage this complexity and can call for more resources and knowledge.
- electricity Consumption: Wireless sensor networks frequently have limited resources, especially when it comes to electricity. The utilization of ensemble-based analytic techniques may necessitate greater computational power and connectivity between sensor nodes, resulting in higher energy usage. The entire lifespan of the sensor network may be considerably impacted by this increased energy usage, so it needs to be carefully controlled.
- Scalability: Because wireless sensor networks can have a large number of sensor nodes, it's important to make sure ensemble-based analysis techniques can scale. The computational and communication cost of ensemble-based analysis may become unreasonably large as the network grows. Assessing if ensemble-based analysis techniques can successfully scale to big sensor networks without noticeably degrading performance is crucial[19].
- Data Dependency: To produce reliable and accurate results, ensemble-based analytic approaches frequently rely on the availability of a variety of complementary data sources. However, issues with data availability, quality, and dependability may arise with wireless sensor networks. In wireless sensor networks, ensuring the availability of adequate and high-quality data sources for ensemble-based analysis might be a considerable challenge.
- Communication Overhead: To carry out the ensemble decision-making process, ensemble-based analysis necessitates communication and data sharing across sensor nodes. In addition to adding latency, this communication cost might use up network resources. The viability of applying ensemble-based analysis in wireless sensor networks must be assessed in light of the communication overhead's effects on latency and overall network performance.

A technique of collaborative decision-making known as "ensemble-based analysis" mixes several models or algorithms to increase the precision, resilience, and dependability of analysis or forecasts. Although ensemble methods have been extensively researched and used in many different fields, little is known about how effective they are in wireless sensor networks. The purpose of this study is to examine the possible advantages and restrictions of ensemble-based analysis concerning wireless sensor networks. In wireless sensor networks, the study tries to improve data analysis, prediction, and decision-making processes by utilizing the collective intelligence of several sensor nodes or algorithms

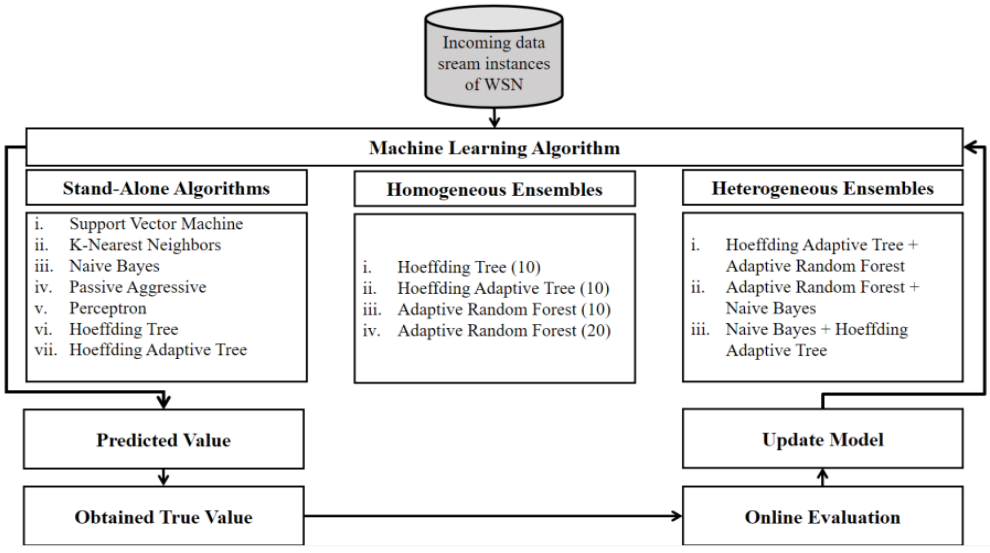


**Fig 2**. The Structure of the Proposed Approach

*Proposed Model*

The suggested gadget examines goals to look into how well ensemble-based total time series analysis performs in wireless sensor networks. This method can combine the indicators derived from several algorithms to better investigate the important variables from the sensor statistics. Additionally, it can help identify patterns and trends in the sensor recordings. Using only the data gathered from the sensors, it can be utilized to forecast future events or occurrences. The system will also analyze how well different tactics forecast an occurrence or predominance, such as linear fashions, non-linear fashions, and their combination with ensembles. Additionally, the system will examine methods to raise the precision of forecasts generated using the various procedures. Additionally, the system will analyze the power efficiency of various methods as well as the hardware and software complexity involved in enforcing the various methods**. Fig 2** shows the structure of the proposed approach.

$$\pi_t = \pi_{1\partial\eta/M} + \pi_{0/S} + \pi_B \tag{1}$$

$$\max_{(pn_1, pn_2, \ldots, pn_{N+1})} \sum_{i=1}^{N+1} pn_i RN_i \tag{2}$$

The results obtained from this device will enhance wireless sensor networks' accuracy and performance in a variety of contexts.

*Power Monitoring System with Wireless Sensor Networks*

An integrated device called the Power Tracking System with Wi-Fi Sensor Networks (PMS-WSN) is made to monitor and assess the energy usage patterns of commercial or industrial buildings. It consists of several Wi-Fi sensor nodes, a primary tracking station, and everyone with the ability to communicate verbally with other nodes.

$$\max_{(pn_1, pn_2, \ldots, pn_{N+1})} \sum_{i=1}^{N+1} \frac{IPN_i}{pn_i} \tag{3}$$

$$\partial_{r,ij} = \partial_{\pi R} Y^2 \left[ \frac{\sigma}{4\delta\left(L_{ij} + B\right)} \right]^2 \tag{4}$$

Data is collected over an extended period from various nodes and examined to determine the sample power consumption. Exclusive electricity assets, such as electricity, natural fuel, and other kinds, of resources, and kinds of power intake, can be distinguished by the system. It enables it to look into and calculate the amount of electricity used over an extended time, as well as identify periods of peak demand and the causes of such peaks in **Fig 3.**

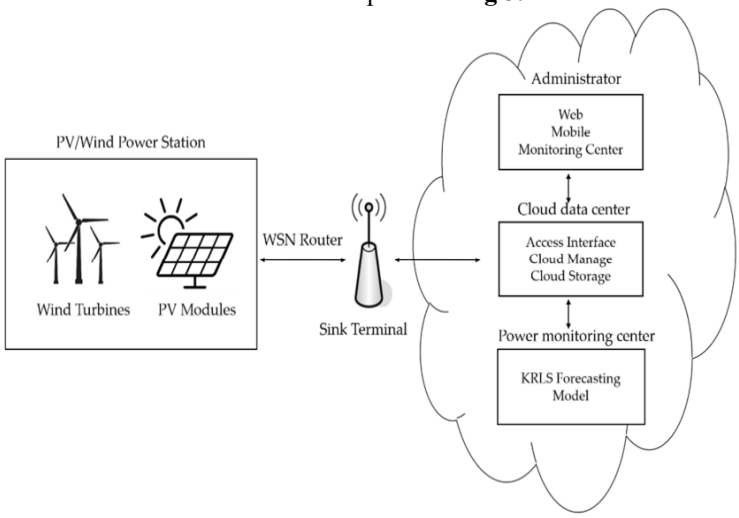


**Fig 3.** Monitoring System based on WSN

Additionally, the PMS-WSN gadget gathers environmental data such as temperature, humidity, pressure, and so on, enabling it to recognize changes in strength according to weather patterns.

$$IPN_i = \sum_{j=1, j\neq i}^{N} \delta_{r,ij} \tag{5}$$

$$\max_{(pn_1, pn_2, \ldots, pn_{N+1})} \sum_{i=1}^{N+1} \frac{\partial \pi_i}{pn_i} \tag{6}$$

Customers can specify thresholds and indications using the graphical user interface (GUI) that powers the system's software. It provides a wide range of forecasting methodologies, from traditional approaches like ARIMA to sophisticated learning strategies like long-term memory networks and recurrent neural networks.

*Proposed Algorithm*

The purpose of this approach is to identify the transient component of a normalized and denoised BT single signal and its characteristics. The program calculates the input signal's energy envelope (EE), which shows the signal's energy content with time.

| **Proposed Algorithm** |
|---|
| IP: Normalized denoised BT single. |
| OP: The transient portion & its features |
| Compute the EE of the IP signal// EE is an energy envelope |
| Starting detection by using an energy envelope |
| For i=1:length(EE) do |
| If T1*mean (EE(I: i=T2))<EE(i+T3) |
| Then start point=i |
| For j=length (EE) :-1: Start point do |
| If mean (EE(length (EE):-1:j-T4))-EE(j)>T5 |
| Assign point j. |
| Max_point=max(EE(j:T6)) |
| Windowing EE(Max_point:length(EE)) |
| For k=1:#windows do |
| If mean(diff(windows k-1))<0&& If mean(diff(window))>0 |
| Then the end point=index of window k(1) |

*Calculating the Energy Envelope*

The input signal's energy envelope must be calculated in the first place. An illustration of the signal's energy over time is given by the energy envelope. Numerous signal processing methods, including the wavelet and Hilbert transforms, can be used for this.

*Starting Point Detection*

The algorithm begins by identifying the signal's transient portion's starting point. The method determines whether the energy envelope at index 'i+T3' is less than the energy envelope at index 'i' for each index 'i' along its length. T1 is a user-defined threshold, and the mean of the energy envelope from index 'i' to 'i+T2' is multiplied by this value. The algorithm regards index 'i' as the beginning point of the transitory section if this condition is met.

*Ending Point Detection*

After determining the starting point, the algorithm finds the transitory portion's ending point. Beginning at the energy envelope's end (length(EE)): The algorithm iterates through each index 'j' starting at index -1. It determines whether the energy envelope at index 'j' and the mean of the energy envelope from length (EE) to index 'j-T4' diverge by more than T5, which is another user-defined criterion. The algorithm designates index 'j' as a possible finishing point if this criterion is met.

$$\max_{(pn_1, pn_2, \ldots, pn_{N+1})} \left[ W_1 \sum_{i=1}^{N+1} pn_i R\eta_i + W_2 \sum_{i=1}^{N=1} \frac{I\partial \eta_i}{pn_i} + W_3 \sum_{i=1}^{N+1} \frac{\partial \pi_i}{pn_i} \right] \tag{7}$$

$$\max_{(pn_1, pn_2, \ldots, pn_{N+1})} \left[ W_1 \sum_{i=1}^{N+1} pn_i R\eta_i + W_2 \sum_{i=1}^{N=1} \frac{I\partial \eta_i}{pn_i} + W_3 \sum_{i=1}^{N+1} \frac{\partial \pi_i}{pn_i} \right] \tag{8}$$

*Maximum Point Selection*

The algorithm chooses the maximum value inside the energy envelope from index 'j' to 'T6' (an additional user-defined threshold) after determining the possible finishing point. The peak energy within the prospective ending segment is represented by this maximum point.

*Windowing*

The energy envelope is thereafter subjected to windowing by the algorithm. Beginning at the energy envelope's maximal point and ending at its end, it generates windows. The user-defined parameter 'windows' determines the number of windows.

*Identification of the End Point*

The algorithm determines whether the mean difference of the differences of consecutive elements within the window (diff(windows k-1)) is less than 0 or greater than 0 for each window 'k' between 1 and the total number of windows. The algorithm designates the endpoint of the transitory section as the index of the first element inside window 'k' if both conditions are met.

*Link Scheduling*

Connector Scheduling in Ensemble-based An effective method for merging a network of Wi-Fi sensors and devices into a single network is time collection evaluation (ETSA). This method makes use of a series of sensors connected by a wireless link and measured using the same kind of sensor. Then, during the duration of the network, timestamps and occasions are synchronized using a link scheduling set of rules. The goal of the hyperlink scheduling method is to identify community nodes that have the greatest impact on the precision of the time-collecting analysis.

$$y_k = \sum_{x=1}^{x_o} \gamma_x y_{(k-3)} + \sum_{z=1}^{z_o} \omega_z u_{(k-z)} + \theta.1 + \propto_k \tag{9}$$

$$y_k = \phi_k^T \beta_k + \mu_k \tag{10}$$

These nodes provide the necessary diversity for the time-collecting analysis depending on where they are placed on the various link levels. The operational principles of the link scheduling algorithm take into account several standards, the variety of sensors that are deployed, their physical positioning and connectivity, and the information charge of each link. The time series evaluation is optimized by the link scheduling method by taking into account the community's facts fee constraints, the latency of the links, and the accompanying delays caused by the packet community site visitors.

$$\phi_k^{\pi} = \left[ y_{k-1}, ....., y_{k-x_o}, \wedge u_{k-1} ..... u_{k-z_o} 1 \right] \tag{11}$$

$$\beta_k = \left[ \gamma_1, ....., \gamma_{xo,} \wedge \omega, ....., \omega_{zo} \theta \right] \tag{12}$$

It makes it possible to decrease the impact of inaccurate events or statistical samples, which may result from utilizing external assets or inaccurate sensor readings.

*Kernel Recursive Least Square Model*

A collection of guidelines for calculating nonlinear regressions and characteristic estimations using a time-collecting dataset is known as the kernel recursive least rectangular version. The usefulness of ensemble-based total time collection analysis in Wi-Fi sensor networks is examined using this method.

$$K_{\phi,\phi^1} = \exp\left( -\frac{\left\| \phi - \phi^1 \right\|^2}{2\rho^2} \right) \tag{13}$$

It enables the community to estimate the preferred output features and capture the nonlinear interactions among the data elements. To construct the kernel recursive least square technique, each fact point in the time series is weighted using a radial basis characteristic (RBF) to create a fixed basis feature.

$$\hat{y}k = \phi_k^T \hat{\beta}_k + \mu_k \tag{14}$$

$$\%F1\pi = 100\left( 1 - \sqrt{\frac{\sum_{k=1}^{N} \left( y_k - \hat{y}_k \right)^2}{\sum_{k=1}^{N} \left( y_k - mean\left( y_k \right) \right)^2}} \right) \tag{15}$$

To take into consideration the correlations between the most recent and older statistical factors, the RBF weights are changed recursively. It enables the version to control its settings and adjust to private settings. Regularization settings are another feature of the procedure that helps prevent the information from being overfitting. By contrasting the ensemble-primarily based forecasts with the ground truth values, the ensemble's efficacy is determined.

## III. RESULTS AND DISCUSSION

A few personal models created by each modeler are combined in the ensemble-primarily based time-gathering analysis, and their combined intelligence is used to replace the forecasts. Together with out-of-pattern accuracy, prediction ability, and forecast dependability, several measures have been established. These measures can be used to identify the best model for a certain set of records and assess how well the fashions function in changing situations. In the future, ensemble-based total time series analysis ought to offer more advanced modeling options in demanding settings, such as disaster management, environment monitoring, and concrete traffic control domains. The wireless sensor network dataset(wsnds from kaggle website) is used here for the simulation process. The Network Simulation (NS-3) is used to execute the results. Table.1 shows the WSN Simulation parameters.

**Table 1.** WSN Simulation Parameters

| Parameter | Value |
|---|---|
| Number of nodes | 100 nodes |
| Number of clusters | 5 |
| Network area | 100m× 100m |
| Base station location | (50,175) |
| Size of packet header | 25 bytes |
| Size of data packet | 500 bytes |
| Maximum transmission range | 200 m |
| MAC protocol | CSMA/TDMA |
| Routing protocol | LEACH |
| Simulation time | 3600 |

*Miss Rate*

The percentage of frames sent by the sensor but not yet effectively obtained on the sink is known as the omit fee. In contrast to the natural diffusion scheme, the ensemble-based total technique's missing charge was altered within the publication. **Fig 4** shows the computation of misrate.

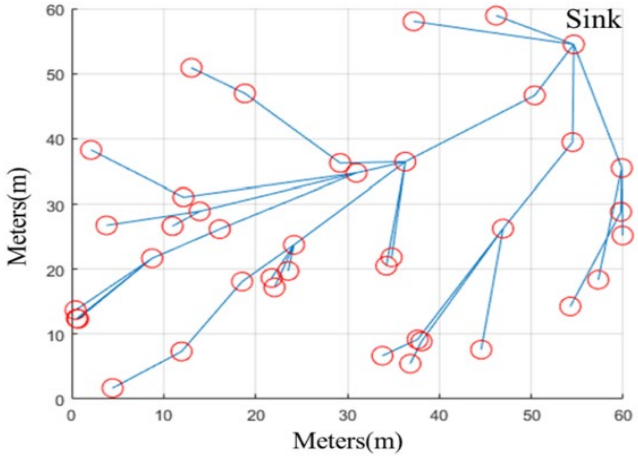


**Fig 4.** Computation of Miss-rate

The results demonstrated the significant increase in miss expense of the ensemble-primarily based strategy, with a mean leave-out charge of approximately 3.5% as opposed to 6.2% for the pure diffusion scheme.

**False Negative Rate**

The range of activities that are correctly predicted to be low quality but are classified as high quality is measured by the fake alerting rate (FNR) of an ensemble-based complete time series evaluation in wireless sensor networks. Stated differently, the FNR quantifies the percentage of false positives among all the adverse events that are accurately anticipated. Usually, the phony negative charge depends on how well the predictive model works. **Fig 5** shows the computation of false negative rate.

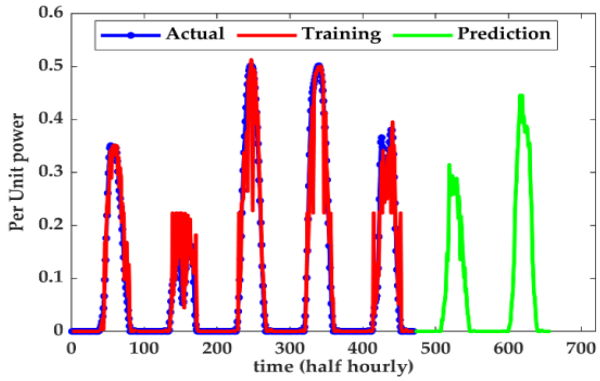


**Fig 5.** Computation of False Negative Rate

It may suffer from things like how well the version fits the data and how trustworthy the fact inputs are. Generally speaking, a higher false negative cost indicates that the predictive model is not looking good. However, a low FNR may indicate that it is far more accurate.

*Fall-Out*

Fallout quantifies the amount of unique dataset that is destroyed after evaluation in ensemble-primarily based time series evaluation in Wi-Fi sensor networks. When dealing with a dataset comprising only a few sensors, it typically indicates the number of sensors removed from the dataset because they were too noisy or had anomalous values. It also shows the extent to which the records set is changed following clustering. **Fig 6** shows the computation of the fall-out.

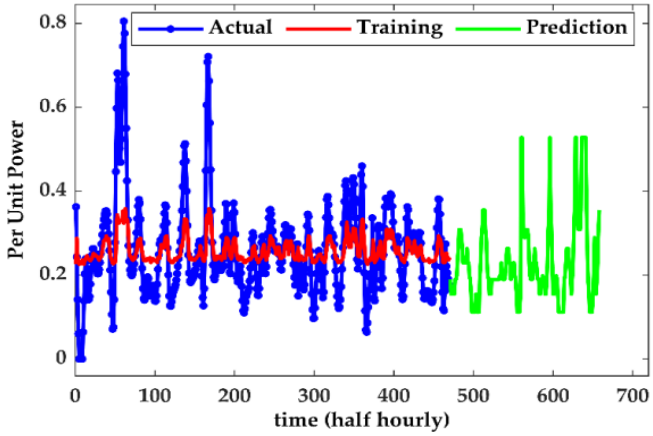


**Fig 6.** Computation of Fall-Out

The efficiency of such analysis can be assessed by comparing the evaluation's results to those of unique ensemble algorithms. There are two ways to measure fallout: absolute fallout, which is the normal number of records deleted after processing, and relative fallout, which assesses changes in the information set following clustering or processing. **Table 2** shows the Comparison of prediction accuracy

**Table 2**. Comparison of Prediction Accuracy

| | **LR** | **TR** | **GPR** | **SVM** | **NN** | **LSTM** | **KRLS** |
|---|---|---|---|---|---|---|---|
| RMSE | 0.04482 | 0.05281 | 0.04555 | 0.05289 | 0.04756 | 0.05969 | 0.04210 |
| R-Squared | 85 | 79 | 85 | 79 | 83 | 74.38 | 88.17 |
| MAE | 0.031053 | 0.036537 | 0.031849 | 0.034726 | 0.032962 | 0.033409 | 0.001800 |
| **Sensor Recognition Accuracy** | | | | | | | |
| RMSE | 0.04482 | 0.052865 | 0.045685 | 0.05289 | 0.01811 | 0.01460 | 0.031384 |
| R-Squared | 52 | 91 | 76 | 69 | 0.02111 | 0.031849 | 0.017044 |
| MAE | 0.085273 | 0.036537 | 0.031849 | 0.034726 | 0.032657 | 0.000211 | 0.038025 |

*False Positive Rate*

The false acceptable fee quantifies the cost at which a sensor's normal reading is mistakenly classified as "odd" by the ensemble-based total time collection evaluation. **Fig 7** shows the computation of false positive rate.

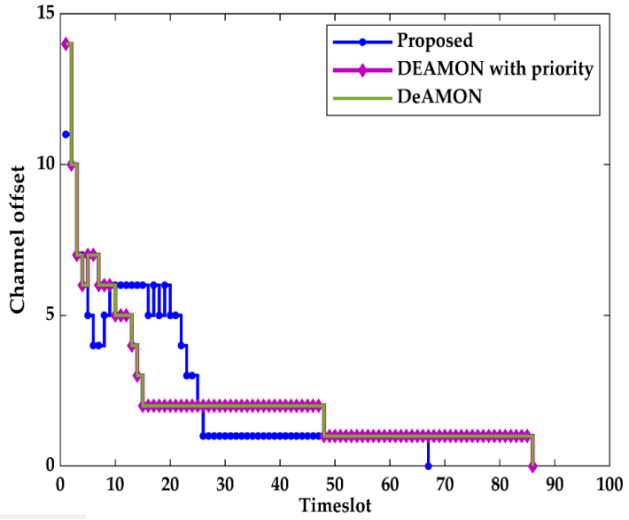


**Fig 7.** Computation of False Positive Rate

This rate is expressed as a percentage and is computed by multiplying the result by 100 after calculating the range of incorrect selections and dividing by the wide range of readings. For the Wi-Fi sensor community, the fictitious high-quality charge is advantageous in evaluating the precision and dependability of the ensemble-primarily based time series assessment employed.

## IV. CONCLUSION

It has been shown that investigating the efficacy of ensemble-based time collection evaluation in Wi-Fi sensor networks has greatly increased the precision of sensing fact prediction and anomaly detection. Furthermore, based on much larger datasets, it significantly lowers the risk of false alarms. This technique is also excellent for improving fault tolerance, energy efficiency, and community operation's overall performance. However there are still some serious issues that pose a risk to public safety. Thus, it is necessary to investigate workable strategies to deal with such issues and also improve the overall performance of ensemble-based time series analysis in Wi-Fi sensor networks. As may be predicted given the dynamic nature of wireless sensor networks (WSNs), ensemble-based total time collection analysis is becoming a potent modeling technique. It has made it possible to deploy WSNs in demanding and dynamic contexts. The main goal of ensemble-based time-collecting analysis is to increase the accuracy of predictions derived from several underlying fashions. If this goal is not met, inaccurate estimates may be produced, which could result in less-than-ideal overall performance. Additionally, it might be possible to create self-adaptive patterns that could regularly swap out the predictions depending on the changing environment.

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**Data Availability**

No data was used to support this study.

**Conflicts of Interests**

The author(s) declare(s) that they have no conflicts of interest.

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**Competing Interests**

There are no competing interests.

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