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An Efficient Machine Learning and Filter Based Implementation of Data Fusion in WSN

Naganna Shankar Sollapure . Poornima G

Department of Electonics and Communication
BMS College of Engineering, Bengaluru, India

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Abstract – Due to the large number of datasets produced by various sensors integrated within various IoT (Internet of Things) applications worldwide, multiple-sensor dataset fusion has become a major challenge in the modern era. In recent years, researchers have developed a variety of solutions for improved data fusion processes for reliable data processing in the IoT and wireless sensor networks (WSNs) environments. However, such existing models have a variety of limitations due to limited design constraints for data processing in IoT-based WSNs. This has indeed been extensively presumed as just the robust non-linear system because of high computational complexities generated in response within the entire functioning. A meticulous and appropriate methodological solution is becoming a difficult task to accomplish. In order to address the aforementioned issues, the authors of this article created an improved model by combining the ML (Machine-Learning) algorithm with the Kalman filter for a more accurate and precise centralized data fusion process in the WSNs environment. Furthermore, our developed model is more energy efficient than previous models due to its lower computational complexity design. In comparison to previous models, the results of the proposed model indicate a gradual improvement in overall prediction accuracy. The proposed model includes precision values of 97.98 percent, 95.12 percent, 97.18 percent, and 97.84 percent for accuracy, F1-scoring, and recall, among other parameters. In terms of performance, all of these parameters outperform the previous model. More investigation into this area for performance simulation of the system on high volume data sources of sensors in the WSNs scenario is possible in the future.

Index Terms – Internet of Things; Data Fusion; Data Processing; Kalman Filter; Machine Learning; Sensor; Wireless Sensor Networks.

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I. INTRODUCTION

Context-awareness, which incorporates environmental monitoring and networking connectivity, as well as dataset analytics approaches, will enable IoT (Internet of Things) to connect the real and virtual worlds over the next several decades. Technology enables a wide range of cutting-edge IoT technologies, such as intelligent medical programs, smart transportation technologies, and reasonable and fair power structures, including intelligent architecture [1]. Intelligent IoT-rooted services, as well as basic IoT sensing technology, are both components of the Distributed system's integrated approach. This same IoT global marketplace anticipates 6.8 billion IoT-rooted applications in 2021, a 22% in crease over 2020. This prediction comes from Gartner. The use of developing innovations such as cloud infrastructure and wire less network technology is also propelling the global growth of the entire IoT-based marketplace. As a result of this growth, the demand for connected IoT equipment and software solutions is rising exponentially [2], [3].

The primary goals of IoT sensory networking are to (a) sense important datasets from the real-physical world outside, (b) sample the overall signals of the internal system, and (c) extracting meaningful datasets from sensor data for correct decision making. The use of a wireless sensor connection by IoT rooted apps should be highlighted. Because of their randomly distributed positioning, such WSNs can create ad hoc networking without requiring a traditional architecture [4]. Low-cost and low-power devices such as Wi-Fi, Bluetooth, Zigbee, Closed Frequency Communication, and many other, support the wireless sensor network.

Nonetheless, such wireless-rooted networks experience difficulties such as inference, dataset loss, redundancy, and various dataset creations. It is obvious because basic sensor data from IoT-based sensors contains significant amounts of untrustworthy and useless information. As a result, in order to extract useful datasets from the cleansed IoT-based sensor datasets, the under- lying sensor datasets must first be cleaned up. Furthermore, a restricted IoT-rooted sensor networking may have higher com- puting costs as well as asset overuse due to an abundance of un- wanted, including worthless information. The most widely used dataset processing methods are dataset denoising, dataset impu- tation, dataset outlier detection, and dataset aggregation [5].

WSN applications have expanded to include organization, financial, defence, and healthcare fields. WSN is currently established to monitor the actual atmosphere as well as find significant occurrences using dozens of sensor networks. Tracing frequently encompasses keeping an eye on as well as locating the attacker's location. One of the fundamental issues with WSN is power constraint. Data transfer from sensor nodes to base stations consumes the most power instead of data processing. The power consumption required to operate sensor networks determines the system longevity. It is indeed impossible to recharge or repair the battery of an individual sensing node after it has been installed. The effective use of detector power is critical for elongating the total network's lifespan [6]. This research offers an improvised model combining the ML- based algorithm and Kalman Filter for IoT based WSNs data fusion to locate but also track mobile targets in sensing net- works. The core of the offered methodology is this cooperative clustering and forecasting method. The suggested solution minimizes unnecessary dataset transfers between the base station and the sensor network in order to conserve electricity. While the base station location is fixed for merely a statistical base station model, this suggested method is tested for both statistical and mobile base station models that move continuously within the sensor node region. This reduces localization errors and finds the exact route to the destination [7].

In sensor fusion, two or more datasets are combined to pro- duce a dynamic network evaluation that is more accurate, con- sistent, and dependable over time. This estimate gives better results than using the detectors separately. The purpose of detector fusing is to decrease cost, device complexities, and element count while improving detection accuracy and trust. The dataset sources, which may be computational methods or detectors, as well as the system status, may comprise velocity, length, etc. The use of sensory fusion is useful for four reasons: (a) it enhances the quality of datasets; (b) it might increase dependability; (c) it might measure unmeasured states; and (d) it might broaden the scope of overall coverage [8].

In general, dataset fusion strategies can be described as stochastic, analytical, knowledge-rooted, comprising judgement as well as argumentation approaches. These probabilistic meth- ods comprise Kalman filtering, Bayesian networking, maximal likelihood estimation methods, decision theories, and others. Example of quantitative techniques include covariance, which includes the crossing variance, and various statistical studies. Examples include artificial neural networks (ANNs), fuzzy-based reasoning, including genetic algorithms, and other knowledge- based methods. Based on this issue characterization, the optimum dataset fusion methods should be chosen. Also, the ML- rooted algorithm's principles and the Kalman Filter fundamentals are addressed.

II. LITERATURE SURVEY

The application of data fusion techniques is challenging for both scientists and system operators due to a number of issues. The untreated defective dataset, which was discussed in an earlier section and whose provenance is extremely uncertain and obscure, was the primary cause of the majority of these issues. Every network administrator has the challenging task of analysing data from numerous channels and extracting information that is useful. The issues with the various datasets fusion system had drawn the attention of several scholars. Some academics have recently used a probability strategy leveraging Bayesian networks to address this dataset fusion difficulty [9], [10].

This method uses the probability density's function (PDF) to depict the degree of ambiguity present in the dataset. Even though one common approach to dealing with ambiguous datasets is effective, it would fall short in dealing with other aspects of the dataset's flaws, such as how to deal with lost dataset samples or dataset correlation [11]. In addition, some earlier researchers [12] used fuzzy reasoning to handle ambiguous datasets and produce selection criteria for the program's user. An embedded architecture utilising fuzzy-set with datasets fusion was applied [13], [14]to decrease the overall chance of failure in any interconnected system components. The primary limitation of fuzzy-rooted systems is that they can only merge hazy datasets [15].

To address the problem without relying on the probability estimate to classify the datasets, O. Yong Kang et al.[16], provided an evidence-based approach. Although other aspects of the dataset's imprecision are not discussed, it does allow for the integration of ambiguous and uncertain data. Because of this, it is useless to combine severely incompatible datasets [17]. Rough sets were used in the set approximation-focused techniques used to handle these multimodal datasets [18], [19]. The key advantage of the rough set is that no additional or prior understanding of things like databases is required. However, it also necessitates some granularity fitting of the data, which lowers its productivity. A key approach for the automatic detection of fake datasets is provided by research that used probabilistic adaptive sensing modelling and sensors verification techniques [20]. However, because it was limited to a few simple and well-defined previously identified breakdown kinds, this paradigm used to have very limited applications. The authors of [21] suggested covariance overlap as yet another crucial undertaking using associated dataset fusion techniques. Although it provides better performance, it also provides stricter correlation estimations and has a limited application in real-time systems.

As the network becomes more complex, these dataset fusion algorithms have encountered new issues [22], [23]. Every network administrator has to deal with a variety of ambiguities, inconsistencies, and faults in the datasets. Once more, finding the effective regulations and figuring out the program's status is a difficult work for an administrator. A network administrator may also need prior knowledge about the detecting item, such as analytical properties or probability measurements, in order to make an effective conclusion [24], [25]. The network has a significant inaccuracy gap as a result of the inefficiency of current sensor fusion algorithms. Thus, a number of delicate but increasingly effective strategies using softer computing are routinely used nowadays to get around the difficult systematic process. The basic idea behind adopting a softer computing platform is indeed to use the training datasets for system classification as well as forecasting [26], [27].

III. METHDOLOGY

Design

The authors created an improvised model using the ML-based algorithm and the Kalman filter to improve the performance limits of the dataset's fusion within the WSNs environment. Figure 1 shows how the suggested improvised model is constructed utilizing a Kalman filter for centralized data fusion and an improved ML-based method. Several sensors are to be used in various locations in the suggested concept. Each sensor is linked to the data centre, which effectively translates the datasets that have been acquired by all of the sensors. The data centre uses the WSNs to transmit the obtained dataset to the sink. The term "WSNs" refers to spatially dispersed sensor networks that monitor, measure, and translate the collected datasets towards a centralized point while also keeping track of the physiological conditions of the entire atmosphere.

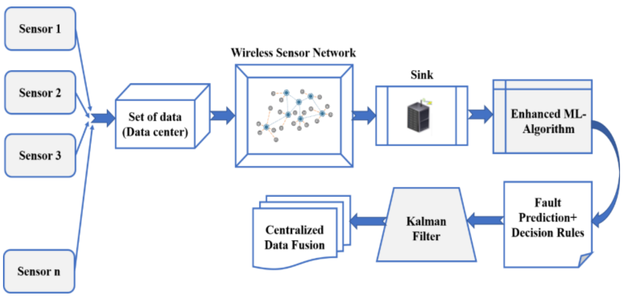

Fig. 1: Proposed model using an enhanced ML-based algorithm and Kalman filter for effective data fusion.

These WSNs are capable of measuring the conditions in the atmosphere, including the sound level, the overall amount of pollution, the current temperature, and many other factors. Each integrated sensor node within the WSNs collects datasets from the installed sensors in real-time and further translates the collected data towards a base station that is nearby, also known as the sink. The improved ML-based system has also

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been used to decision rules and fault forecasts. Next, in the following stage, we included the Kalman filter, which further facilitates the efficient fusing of centralized datasets.

Sensor Data Characteristic

There are many IoT detectors that offer datasets either continually or in reaction to an outside situation. This process entails gathering, aggregating, analysing, and displaying datasets generated by sensor networks to provide datasets that may be used. The actual physical, calculable form and a response to the external triggers are created after further analysis of this data. Many entities provide datasets in addition to those produced by sensing devices. It is necessary to collect and store newly created datasets in an unmatched manner in order to analyse existing datasets. They must also be sent to distant locations at a specific networking datasets rate. Moreover, there are limitations to that, especially with the peculiarities of the sensor dataset. The authors of [28] claim that sensory datasets exhibit informational difficulties as a result of factors including their huge size, dynamic, real-time updates, the ageing of significant datasets, and the dependency between different dataset sources. The sensors are frequently inserted into objects, locations, or people. As a result, the following list contains the essential characteristics of IoT sensing data:

- Technological Constraints: Due to its compact size, this sensor has limited technological capabilities in terms of computer performance, battery life, networking and storage. As a result, many detectors are particularly vulnerable to errors, assaults, and even simple malfunctions, which can lead to massive sensing losses and inaccurate data.
- Real-Time Processing of data: The sensing network would be able to do more complex routine tasks and instantly transform raw sensory datasets into datasets that are more insightful and helpful.
- Scalability: The datasets for this same sensing network are gathered from a range of sensors and processors in the real world. Sensing networks should be flexible to manage the dataset processing needs of IoT-rooted applications which allow the exponential growth of processors and sensors.
- Data Representation: Sensor datasets are frequently packaged into a small, tidy packet. There are several different types of multiple-sensor datasets that are available, including Boolean datasets, binary datasets, featured values, constant data, and numerical values.
- Heterogeneity: IoT sensor data sets come in a variety. Among the different dataset sources are strictly organized datasets, real-time datasets generating information networking, integrated sensing devices, community networking multimedia dataset stream, as well as comparative participatory sensing channels.

Data Collection

The quality and accessibility of sensor datasets, according to researchers from [29], are the main problems with IoT-based sensor networks. Such issues are resolved with dataset mining and analysis techniques from Sensor, including dataset collecting, dataset administration, information finding, and dataset mining. These results, which include decision-making and knowledge development, are attained in these fields through the employment of ML and deep learning-rooted models.

IoT-rooted sensor datasets require an efficient method for gleaning knowledge from datasets, which is why the researchers of [30] investigated the issue. In the context of IoT rooted sensor dataset analytics, ML-based models must be performed within the sensors' embedded CPU. Control the properties of real-time IoT-based sensor datasets; this requires specialized software as well as a strong dataset structure. The researchers proposed an improvised model utilizing a Kalman filter and an ML-based algorithm to manage the many characteristics of sensor datasets. Moreover, continuous ML based algorithms, real-time hardware and software coordination, as well as the categorization of output datasets for IoT-rooted applications, were utilized. Table 1 illustrates the selected stimulation parameters.

Table 1: Illustrates the selected simulation Parameters

Sl. No.	Selected Parameters	Corresponding value
1	Size of the area	300×300 m2
2	Sensing nodes	{50, 100, 150, 200, 300, 500}
3	Threshold limit δ	100m
4	Base station coordinates	50, 50
5	Coverage of sensing	100m
6	Range of Communications	150m
7	Beginning energy	1.5 J
8	Speed of the Target	0−50 m/s

Enhanced ML-based Algorithm

Step 1: Let FS be the group of Fp nodes of the sensor, which are to be deployed within specified sensor networks as well as the base station is positioned over coordinates (50, 50), within the WSNs environment.

$$\mathrm{FS} = \{\mathrm{FS}_1, \mathrm{FS}_2, \mathrm{FS}_2, \mathrm{FS}_3 \ldots \ldots \ldots .. \mathrm{FS}_{\mathrm{Fp}}\} \qquad (1)$$

Step 2: If any selected target is to be determined inside the overall sensing coverage area of the sensing node, in such a case, a particular sensor node immediately translates the original position of the base station via the cluster head.

Step 3: Now, the base station forecasts the subsequent position $\mathrm{Fx}_{k+1}(\mathrm{FP}_L)$ target utilizing the following equation.

$$\mathrm{Cost}\left(\mathrm{Fk}_{k,}\mathrm{Fr}\right) = \frac{1}{\mathrm{FN}} \sum_{\mathrm{Fk}=1}^{\mathrm{FN}} \mathrm{Fv}_r \mathrm{Fr}_{\mathrm{Fk}}^{\mathrm{FT}} + \log|\mathrm{Fr}| \qquad (2)$$

$$\mathrm{Fv}_r = \mathrm{Fz}_k - \mathrm{FH}_{\mathrm{Fr}} \mathrm{Fx}_{\mathrm{Fk}} \qquad (3)$$

Step 4: In this step, the base station translates the predicted position to the activated clustering head. The activated clustering head chooses 3 sensing nodes (FSq) in proximity to the target predicted position.

$$\mathrm{FS}_q = \{\mathrm{FS}_{q1}, \mathrm{FS}_{q2}, \mathrm{FS}_{q3}\}, \mathrm{FS}_q \subseteq \mathrm{FS} \qquad (4)$$

Step 5: Next, the clustering head chooses leader nodes $\mathrm{FS}_L \in \mathrm{FS}_q$ having a greater chosen ratio (FCR) of the energy of residual (FE) as well as via (Fd) from specified targets,

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$$F_{CR} = \frac{FE}{F_d} \quad (5)$$

Step 6: In this step, overall chosen nodes $\{\forall FS_q | FS_q \in \{FS_{q1}, FS_{q2}, FS_{q3}\} \,\&\, FS_q \neq FS_L\}$, determine overall distance Fd via chosen target as well as translate this towards leading nodes i.e., FSL.

Step 7: Now, in this subsequent step, the leading node i.e., FSL estimate the overall target present position utilizing the datasets acquired via 2 chosen nodes as well as its contained datasets.

Step 8: Later, the activated clustering head estimates alteration between the predicted position as well as the present position. This equivalences it along with the pre-set threshold limit δ.

If |Predicted Location-Current Location| > δ

FCH translates FCL to the base station.

Else

None datasets translated via clustering head

The base station saves the predicted location

End if

Step 9: Now again, recurrence of the third step to the eight steps till when the target is to be determined inside the network coverage arena for each 0.7 sec.

IV. RESULTS AND DISCUSSION

The section demonstrates the consequences of mathematical experimentations. The performance computation of the aforementioned ML algorithm has been assessed utilizing MATLAB for a statistical base station prototypical as well as also for a cellular model. Nowadays, effective data fusion is continuously becoming a huge concern in IoT-based WSNs environments. The developed model constructed in the previous years has major limitations at present because of the computing complexity and many other reasons such as low accuracy etc. In this research work, the researchers developed another novel improvised model by utilizing the ML-based algorithm as well as the Kalman Filter.

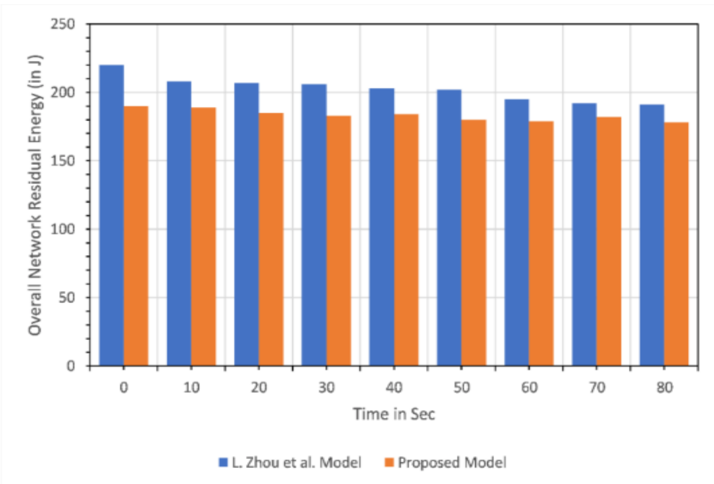

Fig. 2: Illustrates the overall network residual energy (in J) for the proposed model and the existing model.

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Figure 2 illustrates the overall network residual energy (in J) for the proposed model and existing L. Zhou et al. model [31]. The overall network residual energy of the existing L. Zhou et al. Model [31], which shows that proposed model proficient in the modern real time applications based on the IoT-based WSN environment.

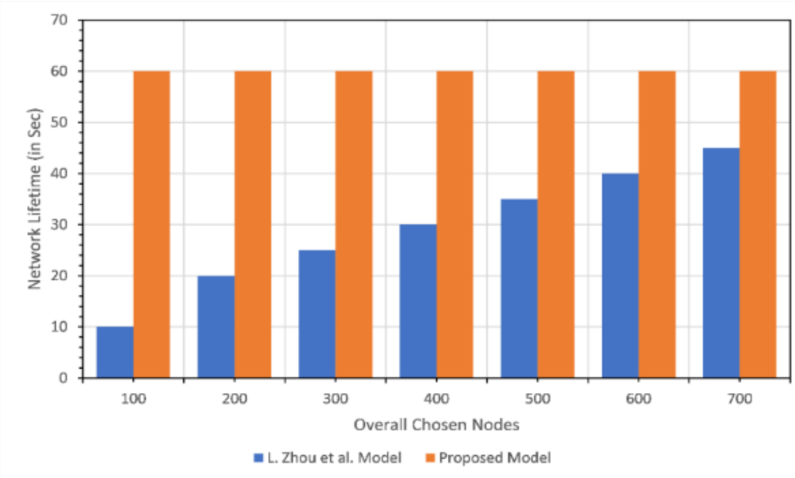

Fig. 3: Network lifetime for the proposed model and existing model.

Table 2: Illustrates the parametric comparison of the suggested model with the existing model.

Sl. No.	Name of the Model	Accuracy (%)	F1-score (%)	Recall (%)	Precision (%)
1	L. Zhou et al. [31]	88.99	89.88	90.45	91.22
2	Proposed Model	98.36	96.36	97.78	98.22

Figure 3. Illustrates the overall selected network lifetime for the proposed model and existing L. Zhou et al. model [31]. The existing model offers the continuous variable network lifetimes on diverse selected nodes. In the proposed model on chosen nodes 100, 200, 300, 400, 500, 600, and 700, the measured network lifetime (in a sec) is to be found constant is 60 seconds, which is optimal and pragmatic in comparison with the existing model. Table 2 illustrates the parametric comparison of the suggested model with existing model L. Zhou et al. [31]. A parametric comparison is done of our suggested model with the existing model to assess diverse performance parameters effectively. For the existing L. Zhou et al. [31] model, the accuracy, F1-score, recall, and precision values are measured at 88.99%, 89.88%, 90.45%, and 91.22%, respectively. While the proposed model offers diverse parameters such as accuracy, F1-scoring, recall, and the precision values of 98.36%, 96.36%, 97.78%, and 98.22%, respectively, which are optimal and improved in comparison with the existing model.

All the outcomes have been measured as well as validated with greater precision as well as accurateness for performance computation of the suggested model and each measured parametric value is measured with existing models for comparative analysis of the proposed model. After the comparison, it is to be found that the suggested model all performance parameters are pragmatic and enhanced in comparison with the existing model.

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V.CONCLUSION

The data processing, data fusion, and sensor integration Dataset analytics grow increasingly advanced as a result of the paradigm change in IoT-based sensor networks towards future technologies like the cloud, fog, and edge computing. Due to the excessive development of heterogeneous datasets from several sensors incorporated into contemporary real-time applications, the fusion of datasets is now a serious problem. Many models that can be used in IoT-based applications have previously been proposed by different authors. However, these current models have a number of drawbacks, including a lower degree of accuracy and precision, which is a major worry and needs increased focus on the creation of new models. The outcome of the suggested model demonstrates that the suggested model is more pragmatic and improved in terms of various performance constraints such as accuracy along with precision. Future study in this area for efficiency calculation of the algorithm on large quantity datasets of the sensors under WSNs environment is possible.

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