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IoT-inspired Framework for Real-time Prediction of Forest Fire

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Abstract

Wildfires are one of the most devastating catastrophes and can inflict tremendous losses to life and nature. Moreover, the loss of civilization is incomprehensible, potentially extending suddenly over vast land sectors. Global warming has contributed to increased forest fires, but it needs immediate attention from the organizations involved. This analysis aims to forecast forest fires to reduce losses and take decisive measures in the direction of protection. Specifically, this study suggests an energy-efficient IoT architecture for the early detection of wildfires backed by fog-cloud computing technologies. To evaluate the repeatable information obtained from IoT sensors in a time-sensitive manner, Jaccard similarity analysis is used. This data is assessed in the fog processing layer and reduces the single value of multidimensional data called the Forest Fire Index. Finally, based on Wildfire Triggering Criteria, the Artificial Neural Network (ANN) is used to simulate the susceptibility of the forest area. ANN are intelligent techniques for inferring future outputs as these can be made hybrid with fuzzy methods for decision-modeling. For productive visualization of the geographical location of wildfire vulnerability, the Self-Organized Mapping Technique is used. Simulation of the implementation is done over multiple datasets. For total efficiency assessment, outcomes are contrasted in comparison to other techniques.

Keywords: Forest Fire, Internet of Things (IoT), Risk Assessment, Forecasting

1 Introduction

Main environmental assets like forests present a critical role in maintaining world ecological equilibrium[1]. Also, forests are important for human life, with the development of extensive resources such as timber, oxygen, and soil[2]. However, wildfire outbreaks have recently engulfed a significant portion of forest land[3][4][5]. 71,499 forest fires were registered in the USA in 2017. In 2017, this resulted in almost 10 million acres (about 4 million hectares) of the protected surface being burnt[1]. Likewise, as per Canada's National Wildland Fire Situation Report[2], about 4,808 forest fires occur per year in Canada, destroying about 2.2 million hectares of wild-cover. As a result, the United Nations Office for Disaster Risk Reduction (UNISDR) announced that in many regions across

[1]Source: https://www.iii.org/fact-statistic/facts-statistics-wildfires
[2]Source: https://cwfis.cfs.nrcan.gc.ca/report

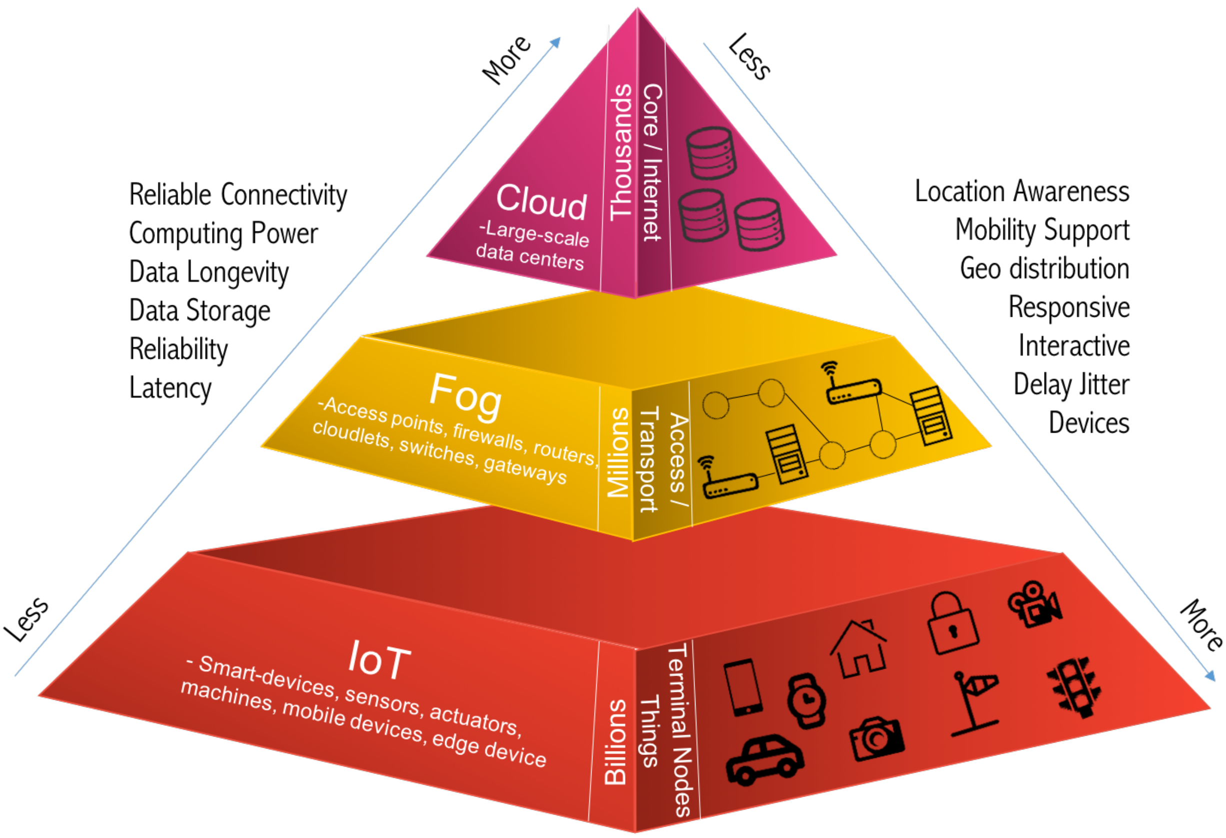


Figure 1: IoT-Fog-Cloud Computing Framework

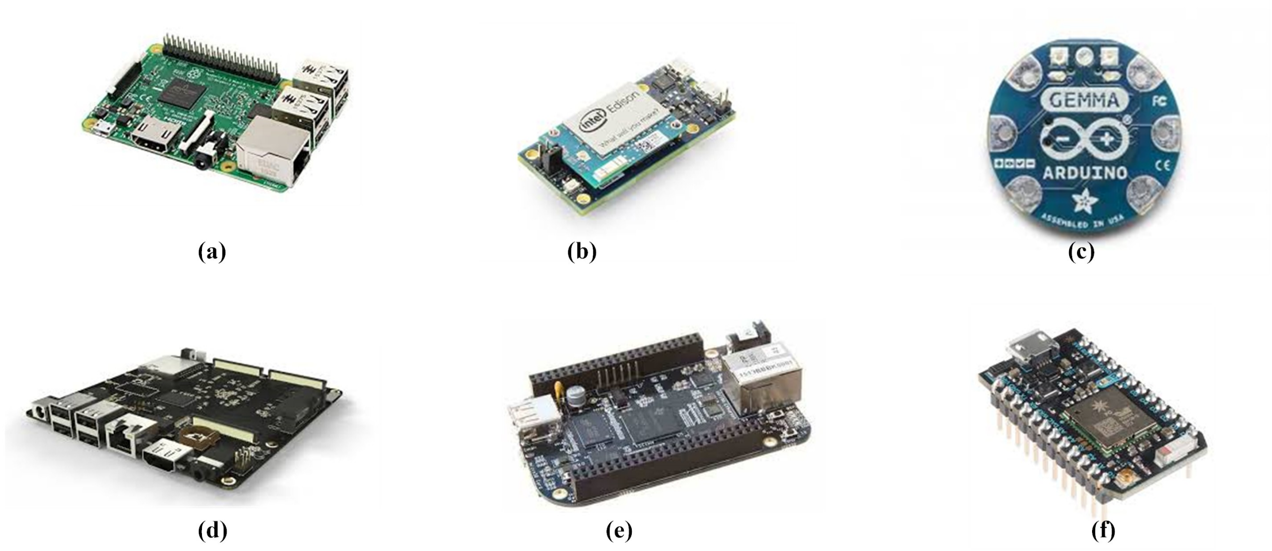


Figure 2: IoT Computing Devices

Table 1: IoT Communication Technologies. (Abbreviations: UWB Ultra Wide band, IrDA Infrared Data Association, NFC Near Field Communication)

Category	**Bluetooth**	**RFID[NFC]**	**IrDA**	**Wi-Fi**	**UWB**
Rate	2.1 Mbps	106 Kbps to 424 Kbps	14.4 Kbps	1 Mbps to 300 Mbps	53 Mbps to 480 Mbps
Band	2.4 GHz	13.56 MHz	850 nm to 900 nm	2.4 G-5 GHz	3.1 GHz to 10.6 GHz
Distance	20-200 m	20 cm	0-1 m	50 m	0-10 m
Network Nodes	8	2	2	50	-
Security	128 bits AES	High	High	High	High
Power (mW)	1-100	<1	-	>1000	<1
Cost(in $)	2-5	<1	-	25	20

the world, forest fire would be recurrent and impactful due to the rise in temperature and droughts condition[6][7]. Also, wildfires have a dramatic impact on climatic environments, soil health, nutrients, and biodiversity in general[8][9]. While researchers have put forward multiple definitions of wildfire, this analysis integrates the widely adopted concept of wildfire by researchers globally[10][11].

Definition 1*: Forest fires are characterized in terms of big flames and impacted by wind, uncontrolled, suddenly escalating and raging, having the potential to wipe vast forest area in quick time.*

The detailed effect of wildfires is given in Definition 1. Despite several heterogeneous influences, the causes of wildfires are divided into two groups[12][13]. They are, firstly, owing to illegal campfires, burning waste, reckless dumping of tobacco, and malicious arson activities, human-induced wildfires[14]. The second class involves wildfires caused by nature, which occur from natural causes[15]. Wildfires are categorized in 3 specific forms based on severity, namely
(i) *Crown fires* are the severely impactful forest-fires that absolutely destroy vegetation,
(ii) *Surface-fires* includes light burn surface which has limited damaging effect
(iii) *Field-fires* that occur in dense humus, peat and dead plant aggregations.
Such wildfires spread steadily, and full containment is incredibly cumbersome. Massive wildfires inflict irreparable and severe harm every year, such as the loss of natural life, habitat devastation, land erosion, air pollution, economic damages, and watershed devastations.

1.1 Research Objectives

The increase in forest fires underlines the critical need for the early identification of wildfires by the planning, monitoring, and tracking of forest areas vulnerable to wildfires[16]. This can be done by the incorporation of the enormous capacity of the Internet of Things (IoT) technology, fog computing, big data analytics, wireless sensor networks (WSNs), and cloud computing[17]. Many IoT sensors are embedded in forested surfaces in the proposed study, constantly tracking the ambient parameters for forest-fire identification. Large amounts of information are produced, requiring real-time processing for detection. Numerous benefits of fog computing, such as low latency, widespread regional variance and minimal requirements for a network, were inspired to incorporate in the presented study. Figure 1[18] demonstrates a 3-layer IoT architecture with numerous devices shown in Figure 2[19]. For prediction purposes, Artificial Neural Network (ANN) has been incorporated. ANN presents several advantages where data segments are involved. Prediction techniques based on the ANN model are significantly enhanced as compared to other techniques. Furthermore, developing an effective cyber-physical system using ANN formulates the core paradigm for the current research. Additionally, researchers around the globe have claimed that the learning behavior of ANN is considerably accurate for parametric prediction in real-time. Conspicuously, it has motivated us to carry out the current research on learning behavior for heterogeneous parameters. The aims of the proposed research include:

1. Wild cover tracking for forest-fire triggering parameters (FTPs) utilizing different IoT devices.
2. Effective use of resources in a constrained environment for increasing the lifespan of the sensor network.
3. Forest fire prediction-inspired by cloud computing platform for real-time data analysis.

Table 2: **Comparative analysis with State-of-the-art Work(Y Yes, N No)**

Parameters	**Williams et al. (2019)**[1]	**Goss et al. (2019)**[2]	**Novkovic et al. (2021)**[20]	**Vikram et al. (2021)**[21]	**Black et al. (2017)** [4]	**Proposed work**
Application Domain (AD)	Forest fire determination	Wildfire detection system	Forest Fire Mapping	Wildfire detection	Smart prediction system	Novel system for wildfire prediction
Major Contribution (MC)	Fir emergency system	Wildfire protection system	Smart Fire Spread Estimation	Monitoring Fire spread	IoT system for prediction	Wildfire prediction system
IoT	Wearable sensor devices	Android application	Sensors	RFID	Wearable sensors	IoT
Cloud Computing (CC)	N	Y	Y	Y	Y	Y
Fog Computing (FC)	N	Y	Y	Y	Edge computing	Y
Alert Generation (AT)	N	Y	Y	Y	N	Alert Based
Prediction Model(PM)	NA	N	TNS-Model	N	N	Advanced ANN
Data storage (DS)	Local	Cloud	Cloud	Y	Local	cloud
Data Mining Technique (DMT)	N	NA	Temporal	RAKE technology	NA	Spatio-temporal
Security Mechanism (SM)	Y	Y	Y	N	N	Y
Visualization (VsL)	Y	Y	Y	Y	N	Y

4. At elevated levels of wildfire vulnerability, emergency warning production is generated for immediate response.

5. Simulation of the endangered land area during forest fires incorporating the technique of Self-Organized Mapping (SOM)

Paper Structure The remaining of the article is formulated in several sections. Relevant literature work about the control of forest fires is given in Section 2. The suggested system for tracking, identification and prediction of wildfires is provided in Section 3. The equipped model's experimental simulations, effects, and performance analysis are seen in Section 4. Lastly, Section 5 ends the paper with a particular significant potential path for science.

2 Related Work

The tracking, prediction, and calculation of IoT-fog-cloud-centred forest fire is a unique conceptualization with tremendous potential. This section offers a short review of some significant literature by various scientists using ICT in the modern area of wildfire monitoring. The bulk of these studies concentrate on service quality and data protection with energy management strategies in applications inspired by WSNs. Yoon et al.[22] also introduced a WSN developed to track wildfires, concentrating on aspects of efficiency and efficiency. For fault-tolerant network configuration, reliable data processing methods ensure data transmission to the base station. Bolourchi and Uysal[23] did related studies in 2013. In wireless architecture, writers introduced a forest-identification mechanism utilizing fuzzy-concept. The fuzzy technique for calculating the likelihood of forest fire is presented using five membership functions, including humidity, smoke, light, temperature, and size. In 2014, an effective architecture for time-sensitive forest-fire identification using mobile agents was proposed by Trivedi and Srivastava[24] (MAs). In 2014, Zhao et al.[25] suggested a fascinating data cumulation using multiple sensors based on the Dempster-Shafter principle and adaptive weighted fusion algorithm (AWFA) for

Table 3: Forest Fire Attributes

S. no.	Forest-Fire Triggering Parameters (FTPs)	Detail
1	temperature	It is the temperatur value measured at the instant of time
2	Month	It is the calender month
3	Precipitation	It defines the quantity of rainfall and snowfall that a particular forest receives
4	Duff moisture code (DMC)	It is the average moisture content of the given area
5	Relative humidity	Amount of humidity at the particular instant of time
6	Initial spread index (ISI)	It is the rate of forst fire spread of a particular area
7	Wind speed	The rate of wind speed in the forest
8	Drought code (DC)	It indicate the drought value of the given area in the forest
9	Fine fuel moisture code (FFMC)	Fuel content of the given area

the wildfire warning method. Ulucinar et al.[26] suggested a smart framework of forest fire detection in which temperature and humidity are comprised of sensor nodes. In addition, a temperature-based fire detection algorithm was suggested by the authors. For the presented methodology, enhanced output was documented upon implementation. In 2015, various machine learning algorithms were surveyed by Kansal et al. [27]. This includes linear regression, SVM, ANN, and wildfire determination decision modeling. In addition, a fire estimation algorithm for the acquisition of resulting data has been presented based on linear regression. MolinaPico et al.[28] proposed a network of sensors for wildfire determination in areas vulnerable to burning. The framework submitted consisted of fire-fighting agencies, fire simulators, and a geographical information system (GIS). A comparative study of several IoT networks and WSN frameworks was conducted by Mina and Ziade[29]. The authors considered parameters such as power usage, the complexity of sensor-hardware, latency, efficiency, and accuracy. On this basis, for wildfire monitoring, consisting of three-phased network topology and IoT devices, a WSN is proposed. Saoudi et al.[30] suggested an IoT network in which, utilizing data analytics technique, every sensor node detects fire. The device sends an emergency warning to the destination sink via the cluster head to warn the firefighters about wildfire when the fire is observed. A wireless sensor node architecture with minimal power consumption was proposed by Abdullah et al[31]. The Low Power Wireless Ground Sensor Network (LPWGSN) was included for seamless forest monitoring and fire detection based on sensory inputs. A self-organizing fault-tolerant framework for early wildfire determination was proposed by Giuntini et al. [32]. Authors supported inter-node contacts that control the area and organize activities via a supervisory node to assess fire early. Lin et al.[33] proposed an algorithm focused on big data analytics to determine wildfire threats and measure their computational ability. A 2-tier Sybil Attack determination framework for hierarchical WSN implementation was presented by Jan et al.[34] for forest wildfire monitoring. High-energy nodes are initially designed to identify the Sybil nodes and their respective forged identities. In cases where one or more personalities exceed the first tier, two end stations can detect them. Toledo-Castro et al.[35] presented an IoT network for the tracking and protection of wildfires about multiple channel techniques and fuzzy-inspired forest-fire vulnerability controller.

2.1 Research Gaps

Based on the comprehensive literature review, numerous research gaps have been identified in the current research. Some of the vital gaps have been identified and addressed in the current work.

1. Even-though work has been done for forest fire prediction; minimal work is performed for the probabilistic prediction using machine learning conceptualization.

2. No work has quantified the parameters for the prediction of forest fire in real-time. In the current study, this is achieved using Forest Fire Index measure instead of, described in Section 3.

3. Visualization is another domain where other researchers have contributed minimally. It presents a major contribution to the current research in the current domain of study.

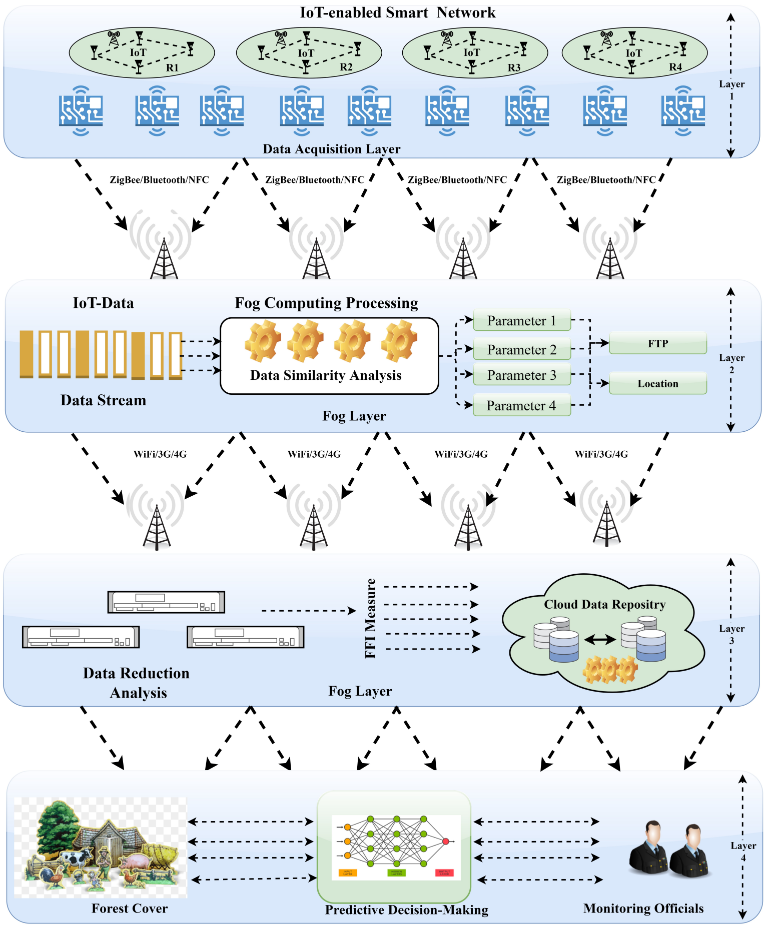


Figure 3: **Proposed Framework of Forest Fire**

4. IoT has been incorporated by researchers for data acquisition, but little work is done to acquire ambient parameters for forest fire estimation.

Based on the mentioned above gaps, a comparative analysis is shown in Table 2.

3 Presented Approach

The layered framework of the presented wildfire risk research strategy is shown in Figure 3. Every layer has specified features for precise wildfire identification. The mechanism proposed was composed of three layers. These involve the awareness layer of records, the layer of fog computing and the layer of cloud storage. The perception layer of data consists of various IoT devices to track a wildfire forest cover triggering parameters (WCPs). Using suitable transmission technology, the acquired data is transmitted to the fog computing layer. Table 1 offers several networking protocols[9]. Such nodes conduct data processing to provide efficient energy consumption for sensor nodes that are limited by resources. In addition, data dimensionality at the fog layer is reduced before further processing at the cloud storage layer. The cloud computing layer calculates a forest block's current wildfire susceptibility and long-term wildfire prediction. In addition, detailed data on wildfires and the effects of the study are stored in the cloud layer, helping to take precautionary steps during forest fires of variable size.

3.1 Data Acquisition Layer

Since the techniques are vital in triggering wildfires, a successful forest-fire identification technique relies on detailed data on various forest-fire triggering parameters(FTP). This layer accumulates vast amounts of FTP's basic information. Many lightweights, cheap IoT gadgets installed in the wildfire cover have carried out this research. After a pre-fixed time, IoT sensors seamlessly detect, collect,

Algorithm 1 Energy Conservation Layer
Input: Sensor values for recent period of t1 and t2, current node, Estimation of similarity, Threshold
Step 1: Determine the sensor node value for for previous 2 readings
Step 2: If Battery is greater than 0, it indicates node is still alive
Step 3: Current node value is set to active
Step 4: Determine the similarty between data values using intersection
Step 5: Set similarity value as cardinality of 2 data values
Step 6: If similarity is greater then threshold, Delete previous data value
Step 7: Wait for activation of node
Repeat steps 1-7 for given time window
Output: Unique data values

Algorithm 2 Data Reduction Layer
Step 1: Input environmental paramters of humidity, speed, precipitation. Constants are selected for weight association, and thresholds are defined.
Step 2: Initialize Index Value to 0
Step 3: Compare the parameters of humidity, temperature, pressure with the respective threshold values
Step 4: If the values are greater then respective threshold values than add the concerned weight to the Index Value
Step 5: Add the weights to compute the final Index value
Output: Index value for the given time window

and transfer measures of FTPs. In addition, geographical positioning criteria defining future wildfire epicenter spatial coordinates are vital in minimizing severe wildfire impacts. The obtained data were divided into 2 groups :
(i) *Dataset of FTPs*
This involves various demographic factors such as rainfall, temperature, relative wind speed, and humidity. In addition, in this dataset, FFMC (Fine Fuel Moisture Code), DC (Drought Code), ISI (Initial Spread Index), and DMC (Duff Moisture Code) have been obtained.
(ii) *Dataset of Location*
This provides geographic, geographical locations of possible wildfire areas. These include, in other words, spatial coordinates with the vertical and horizontal axis.
Table 3 contains, along with its requirements, a list of various FTPs. For further review and processing, the acquired dataset is forwarded to the Fog layer.

3.2 Fog Layer

This layer is sandwiched between data acquisition and the proposed model's cloud computing layer. The utility of collecting and pre-processing an unstructured and missing datum by intelligent devices from the acquisition layer is entrusted. The fog layer is split into two sub-layers within the current scenario, including the model adaptive sampling layer (for similar value identification), the layer for energy preserving, and the layer for minimizing data dimensions.

3.2.1 Adaptive Sampling and Energy Preserving layer

Energy preservation is vital to deploying a framework with humongous IoT devices, particularly in wildfire environments where there can be significant obstacles to battery and power supply. IoT devices generally acquire identical values for FTPs such as wind speed, temperature, and humidity within a specified time instance during environmental monitoring. It becomes a vital aspect to remove duplicate sensor readings to minimize energy consumption during data acquisition and reception. This is achieved by utilizing Jaccard similarity in the adaptive sampling rate. The Jaccard similarity is based on redundancy formulations for redundant records determination. For successive periods, the presented model uses the Jaccard similarity function for determining the redundancy between acquired data values for changing the data acquisition rate based on redundancy value. The Jaccard similarity value is in the range of 0 to 1 value, with 1 depicting maximum similarity and 0 showing different data values. Conspicuously, the datasets with close to 1 similarity value are redundant, and the value of 0 Jaccard similarity depicts different data. The total number of datasets describes the Jaccard similarity function of Di and Dj datasets as the size of the intersection

$JaccardDtj=\frac{kDi\cap Dj}{kDi\cup Dj}$

Where tj determines the minimal measure that the domain expert pre-fixed. Also, as IoT used to acquire environmental data sets are periodic in nature, it is, therefore, possible to describe the acquired data set by the ith IoT-node within a given time-span as (D1, D2,..., Dn), Where Dn denotes nth data value intercepted by the data set vector formulation for the ith sensor at specified instances. Additionally, three additional tasks are analyzed to determine intra-node data collection and reduce duplication efficiently. In certain examples, a specific formulation, including *Overlap, Behavior, and Weighted Cardinality*, has been utilized for evaluating the similarities among measures in the dataset.

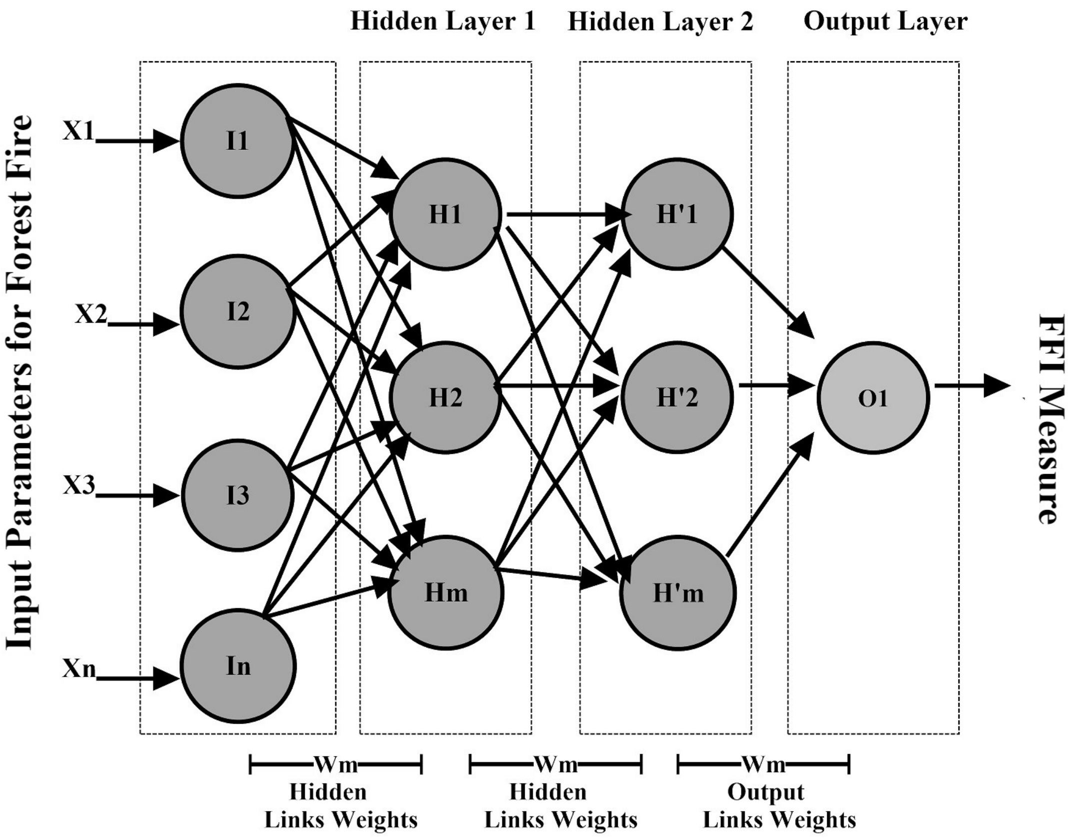


Figure 4: **ANN Architecture for Prediction(x1, x2,...,xn are the input IoT values; o1 is the final ouput of FFI measure)**

Definition 2 *Behaviour is described as the degree of vitality of the data value acquired at the specific instance. Its range lies from 0 to 1. Moreover, its parabolic and hyperbolic form oscillate where the X-Y axis depicts the data value and temporal sampling rate.*

$Behavior=\frac{ty-2Dy}{4px2}Di+\frac{px}{py}Di$

The Behaviour function's input dataset differs according to the Jaccard similarity and cardinality of the dataset as described ahead.

Definition 3 *With a given temporal span $D\Delta t$, weighted cardinality of the data vector D is described as the accumulation of measurements of every sample frequency of the data. Mathematically, it is computed as*

$Cardinality\ D\Delta t=\sum weight(Dk)$

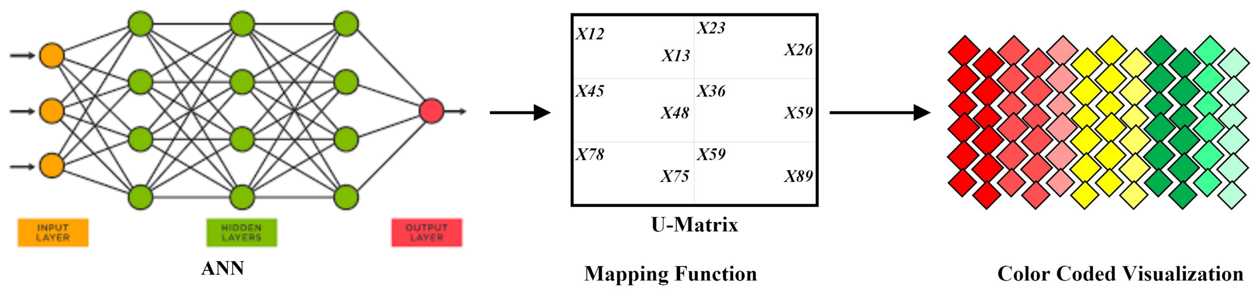


Figure 5: **SOM Model for Visualization**

Where the weight of every data instance calculated is denoted by weight(Dk).

Definition 4 *Overlap is described as the similarity between the 2 data vectors (D1, D2) based on data measures reported in the temporal window. Numerically, it is computed as*

Overlap $(Di \cap Dj) = di \cap dj \ \forall i,j \in Dn$

Similarly, the overall function is computed for every data value acquired as a fog computing layer at a given moment in time. The methodology of data reduction is formulated based on the study of similarities. In Algorithm 1, different steps of the technique are described.

3.2.2 Data Reduction Layer

IoT sensors distributed across forest cover in wildfire tracking accumulate heterogeneous data formats. Also, it is difficult to relay them over the transmission network, with vast data instances collected in the specific time frame. The critical aspect is that the data elements be minimized or compressed for reliable data for processing in a time-sensitive manner. The current research uses the weighted attribute-specific data compression method to reduce the size of the data and preserve data accuracy at the same time. Besides, the gross data cost at the back-end is minimized by such minimization. The attribute utilized for compression is the Forest Fire Index(FFI) in the presented framework. FFI represents a unique decomposed measure dependent on the priority or weighted mean of various WCPs combined for wildfire tracking for the obtained data segments. In addition to this, FFI would enable successful analysis at the cloud layer for prediction and warning generation. Algorithm 2 assesses the importance of the FFI of the forest fire. Also, for this study, four essential parameters are used to determine the FFI value, including temperature, wind speed, humidity, and precipitation measure. Threshold values derived by an authority in the domain are pre-determined.

3.3 Forest Fire Predictive Analysis

As a result of the limited capacity and computing power at fog nodes, deep data analysis for prediction purposes is difficult to do. The cloud layer is also used for the collection and analysis of accurate data for prolonged predictive analysis. This layer is broken into 2 primary layers for simulation with an appropriate prediction model to assess the importance of wildfires. Secondly, for presenting purpose, the visualization layer. Both sub layer's comprehensive functionality is addressed in advance.

3.3.1 Forest-Fire Prediction Layer

This layer's major objective is to conduct effective forecast analysis using enhanced prediction techniques for early wildfire determination. The Artificial Neural Network (ANN) is the tool used for prediction purposes. It is a powerful detection paradigm for early-stage identification of particular importance. Also, it is the most common artificial intelligence technology and is utilized for several applications by different researchers for prediction purposes. ANN consists of separate neurons in the initial layer, the intermediate layer, and the result layer, as seen in Figure 4. Additionally, ANN has the capacity for simultaneous training, monitoring, and learning. It is composed of 3 sub-layers, including Tracking, Learning and Forecasting.

Sub-Layer 1: Tracking
The mechanism by which the ANN technique predicts the FFI is called the tracking layer. It initially includes assigning measures to various FTPs using geo-location. Moreover, these measures analyze the significant factor for forest fire attributes based on the wildfire region. The initial values include multiple FTPs cumulation.

Sub-Layer 2: Learning
Acquisition of different FTPs is accompanied by process of learning where measurement errors are created and removed. ANN uses the feed-forward/feed backward strategy for this purpose. The feed process requires a mechanical translation between input and output transformations based on the allocated measures and triggering function. The calculated value for evaluating and decreasing the error rate is compared with the real value. If any, the error produced is minimized using the technique of back-propagation, controlled by complicated numerical procedures. The whole process is iterated for n times before the error rate achieves equilibrium. Mathematically, ANN's learning process is seen ahead.

$$FFI = \sum_{i=0}^{N} Xb_1 (\sum_{j=0}^{N} Xb_2(X_{ji}) + b) + b$$

Where FFI is the expected forest-fire FFI value of a particular forest cover in a given time window Dt; X is the input vector with the number of elements J; b1(.) is the activation function used to convert the input layer and the output layer; b2(.) is the activation function between the hidden layer and the output layer; Xji is the weight allocated to the input layer jth neuron and ith neuron. By changing the weights associated with connections, the ANN can decrease the discrepancy between expected and real wildfire susceptibility stages. The hidden layer uses a transformation function that is mathematically expressed as follows: The output layer uses a pure line transfer function that is denoted mathematically as follows:

$$b_1(x) = transig(x)$$

$$b_1 = prelin(x)$$

Sub-Layer 3: Forecast
ANN is referred to as trained as soon as the faults are reduced to a certain degree of approval. An equipped ANN is used at a given time to forecast the FFI value for wildfire occurrence. Wildfire forecast provides for the quantification of the assessment of risk based on surrounding conditions and FTPs.

3.4 Visualization layer

Many environmental factors such as temperature, humidity, engagement, and wind speed can cause a wildfire. These elements play a crucial role in wildfires through the broad land cover when accounted for together. Therefore, the monitoring of these variables presents a significant problem for surveillance organizations. To this end, the proposed paper integrates the methodology of self-organized mapping (SOM) to accurately assess and simulate the forecast of wildfires in a time-sensitive manner. SOM approaches ensure color mapping for forest cover based on the FFI measure. The conversion of ANN to SOM is performed using U-matrix conceptualization. In U-Matrix, the distance between the neurons is mapped onto the color-coding. The dark color depicts less space, and more stretch is characterized by light color. Three shades are being used in this study. This includes, in real-time, Red for extreme FFI value, Yellow for medium FFI value, and Green for low FFI value. Forest blocks are divided into three distinct areas depending on the color-coding scheme. This includes the highly susceptible zone,

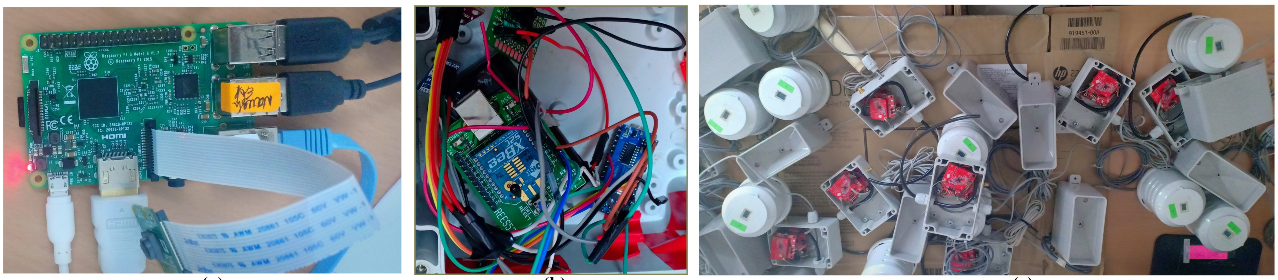

(a) (b) (c)

Figure 6: **IoT devices used for Monitoring; (a) Raspberry Pi; (b) ZigBee module; (c) WiSense Nodes**

the medium-sensitive zone, and the low-sensitive zone. Such zonal categorization helps the monitoring organizations and the wildfire authority to inspect the large cover efficiently. The color-coding process used in this technique is represented in Figure 5.

3.4.1 Cloud Storage

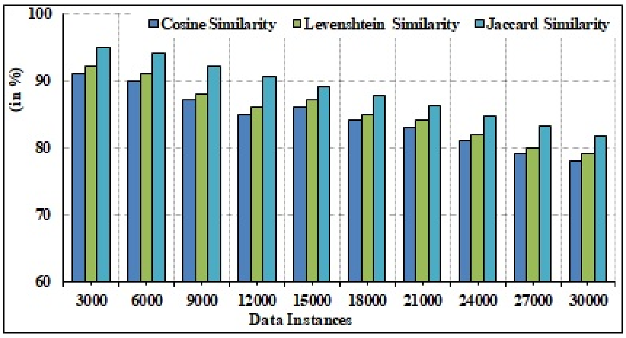
Another primary purpose of cloud data management is data preservation and knowledge regarding wildfire incidents, forest fire patterns, atmospheric patterns vulnerable to fire. As such, knowledge will contribute to successful precautionary steps by the emergency relief agencies involved. With wireless access to historical records, it is possible to stop numerous wildfires with limited destruction of natural resources. Besides, stored data is globally assessed at the cloud level, enabling, where necessary, global wildfire prevention initiatives, policymaking, and life protection.

4 Experimental Implementation

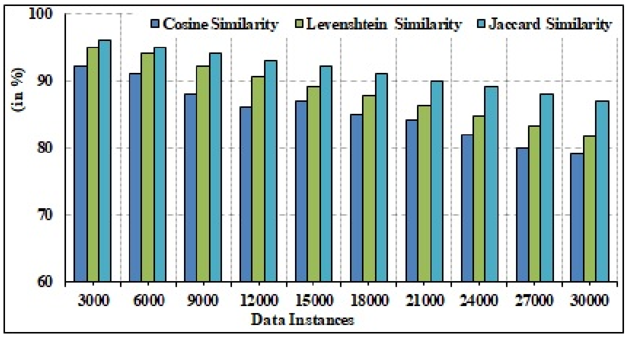
This section conducts a statistical review of the proposed wildfire prediction model to determine output aspects in the simulation setting. Three main layers are used in the current model of wildfire prediction. Data is initially collected using IoT sensors in an energy-conservative system for FTP tracking. Next, the data values are reduced and abstracted for wildfire vulnerability estimation. Finally, the ANN model is utilized to test wildfire adversity to estimate the FFI value for forest-fire prediction. Experimental simulation of the proposed method is provided based on these four measures to execute
(1) Data Similarity Analysis
(2) Wildfire vulnerability forecast analysis
(3) Study of temporal delay
(4) General study of device stability
(5) Reliability Analysis
The findings are contrasted with different state-of-the-art techniques for a comprehensive evaluation of the proposed forest-fire identification model.

4.1 Data Generation

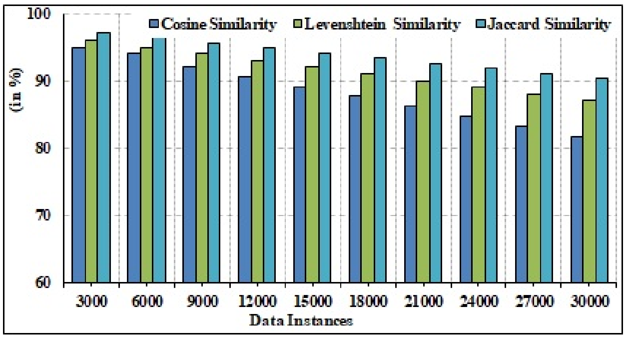
WiSense devices are comprised of multiple environmental tracking gadgets by which wildfire FTP values are obtained. These data sets consist of wind speed, temperature, humidity, and precipitation FTPs for India's 4 Punjab forest divisions. These include Amritsar, Jalandhar, Batala, and Gurdaspur. For each parameter, data values compute to almost 4569 data values aggregating to 18,276 data values. The Intel Corei5 computer with a processor of 3.2 GHz quad-core and RAM of 16 GB is used for experimental simulation. Various Raspberry Pi versions of the fog nodes and XBee module for network connectivity. Fog nodes with 1-3 G cycles/s node processing power and computing intensity of 350 cycles/bit were used (Figure 6. For cloud computing, two virtual CPUs were used for the Amazon EC2 cloud.



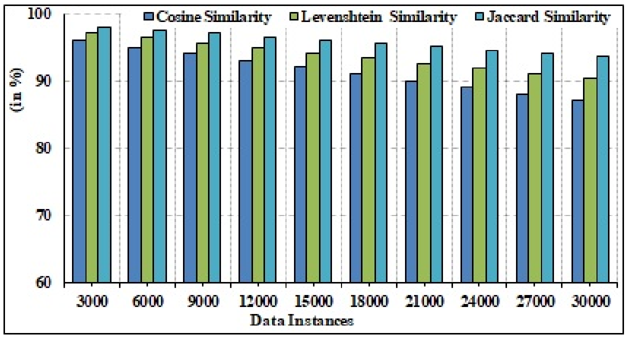
(a) Specificity



(b) Sensitivity



(c) Accuracy



(d) F-measure

Figure 7: Similarity Analysis

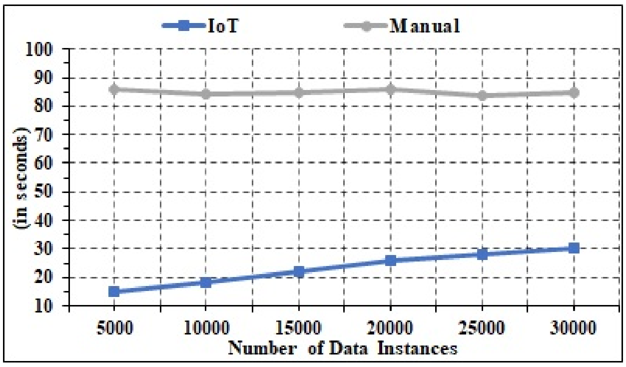
4.2 Data Similarity Analysis

Data similarity analysis is used to identify the effectiveness of using Jaccard Similarity in the current domain for data reduction. The effectiveness is calculated in terms of performance parameters of Sensitivity, Specificity, Accuracy, and F-measure. The four categories of categorical data values used to evaluate these measures are positive (more similar), negative(less similar), false positive, and false negative.

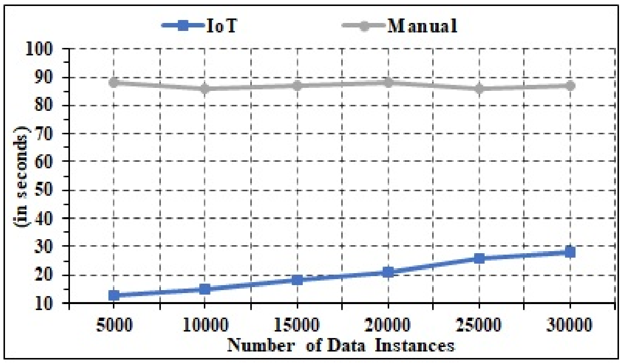
1. Number of positive data values.
2. Number of negative data values.
3. Number of positive data values for false.
4. Number of falsely negative data values.

Results Figure 7 depicts plots of these statistical performance estimators. The comparative analysis is performed concerning Levenshtein similarity and cosine similarity. The detailed analysis is depicted ahead.

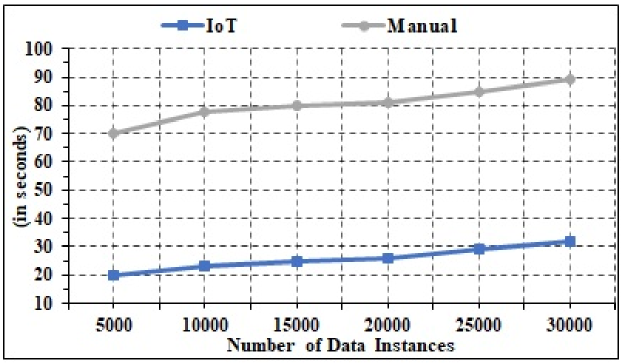
1. The statistical evaluation of specificity is shown in Figure 7(a). In terms of the number of datasets, the plot indicates asymptotic behavior. As more data is included, performance increases. For the given circumstance, however, the presented redundancy technique outperforms existing data reduction techniques. The sensitivity of the presented technique is averaged 95.39%, which is the highest among other methods. It demonstrates the superiority of the Jaccard similarity-based reduction in the current case.
2. Sensitivity measure for the data is shown in Figure 7(b). The plots depict the overall character of the results. The presented technique has a specificity of about 97.26%, higher than other state-of-the-art data reduction models. It indicates enhanced model performance.



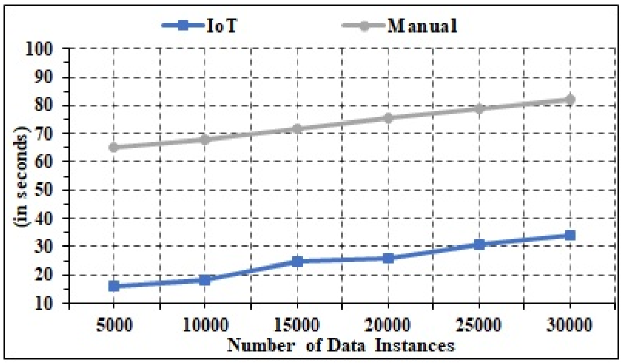
(a) Amritsar Division



(b) Batala Division



(c) Gurdaspur Division



(d) Jalandhar Division

Figure 8: Temporal Analysis

Table 4: Performance Analysis

Parameters	**SVM (%)**	**LSTM (%)**	**DT (%)**	**Proposed ANN (%)**
Accuracy	92.99	94.12	93.14	96.78
Sensitivity	90.12	91.45	90.98	96.45
Specificity	91.98	90.45	95.15	94.78
F-measure	92.15	91.45	93.15	95.15
Mean absolute error (MAE)	4.45	5.17	6.34	3.15
Root mean square error (RMSE)	3.19	2.32	2.45	1.24

3. Accuracy of data is depicted in Figure 7(c). This type of analysis was examined in the segmented form to estimate it. In comparison to existing models, the presented model outperforms them with a 91.23% accuracy. As a result of these findings, the proposed technique outperforms other techniques in the current context and is thus a good fit for the suggested model.

4. F-measure is another important parameter for estimation. In the current context, Jaccard similarity registered enhanced measure of 94.32% which is better in comparison to other techniques, depicting superior performance(Figure 7(d)).

4.3 Forest-fire Prediction Assessment

The suggested wildfire prediction mechanism uses the ANN methodology for research and prediction. Six criteria are used to determine the effectiveness of ANN: precision, sensitivity, accuracy, F-measure, root mean square error (RMSE) and mean absolute error (MAE). Several predictive techniques have been integrated for comparative study. Long Short Term Memory(LSTM), Support vector machine (SVM), and Decision Tree(DT) are among others. Noteworthy that only the prediction model has been updated for comparative study, while the remaining model has kept the same. In Table 4, the findings obtained are shown. In the present situation, relative to 93.79% (DT), 93.16% (SVM), and 95.36% (LSTM), ANN reports a precision of 95.32%. In comparison, ANN registered high values

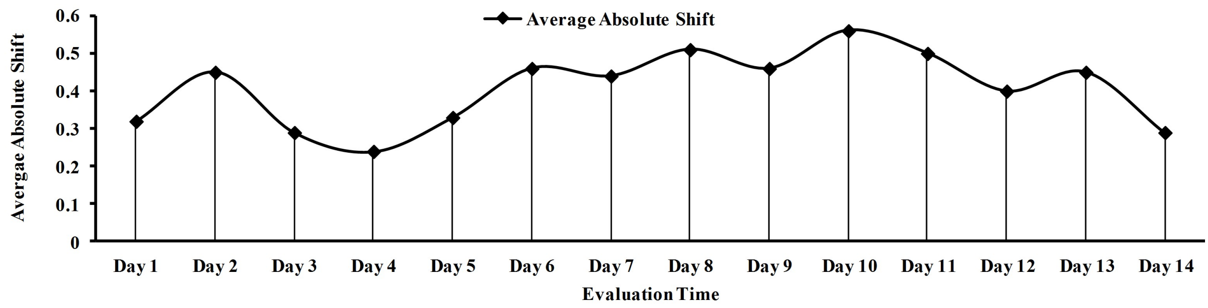


Figure 9: **Stability Assessment**

of 92.36%, more than 92.38% of SVM, 91.11% of LSTM, and 90.65% of DT, for sensitivity values. Similarly, ANN was able to outperform other strategies for precision and F-measure and observed high values of 93.69% and 94.98%, respectively. These observations indicate that ANN is more vigorous and, therefore, more successful in the current scenario. Moreover, for error analysis, in contrast to other methods, ANN also reported low error rates. In particular, an average value of 3.78% for ANN was reported for MAE, and 4.12% (SVM), 5.98% (LSTM), and 6.20% (DT) were acquired for others. Similarly, in contrast to other state-of-the-art models, ANN received limited importance for RMSE. It can be inferred that the presented methodology is highly efficient and reliable for wildfire prediction in forest regions.

4.4 Temporal delay analysis

The time at which data is sensed and processed in the data repository concerns Temporal Latency. Since wireless networking is used for the transfer of data, temporary information is used. When assessing the overall efficacy of the system, delay plays a significant part. In other words, data collection, preparation, and estimation are time-sensitive and essential for performance analysis. Also, network capacity is another critical problem that must be resolved in real-time to deliver big data. For various parameters, results are obtained and are shown in Figure 8. It can be seen that as the number of data values grows, the temporal delay curve increases. However, regarding the manual sensing of data values, the time interval records a mean value of 3.18s/datum, while the manual process records an average value of 16.29s/datum. The presented wildfire prediction strategy is temporarily successful in the current scenario, relative to the manual tracking process.

4.5 Comprehensive Stability Analysis

The proposed method of forest-fire identification is also evaluated for stability determination, in addition to the findings obtained previously. The total device consistency over the number of datasets for acquiring a certain degree of precision is determined by stability estimation. In terms of average absolute change, it is registered (AAS). The higher AAS value represents the technique's erratic behavior, while lower values suggest high device stability. AAS measure for the different number of data instances was registered in 0.16-0.49 depending on the results, averaging 0.29 (Figure 9). The limited AAS measure that the system presented is a highly stable model.

4.6 Reliability Analysis

The overall performance of the suggested model is the central aspect of the reliability analysis. The results of the dependability study are compared to those of several state-of-the-art decision-making systems. Only the decision-making model is changed to assess the proposed model's improved performance, while the rest of the framework stays the same. The reliability of cumulative datasets has been tested using 10% faked data. Figure 10 shows the reliability analysis results that were obtained. As demonstrated, ANN-based decision-making superseded other comparable models in the given circumstance, with average dependability of 83.26%. In comparison, LSTM achieved average

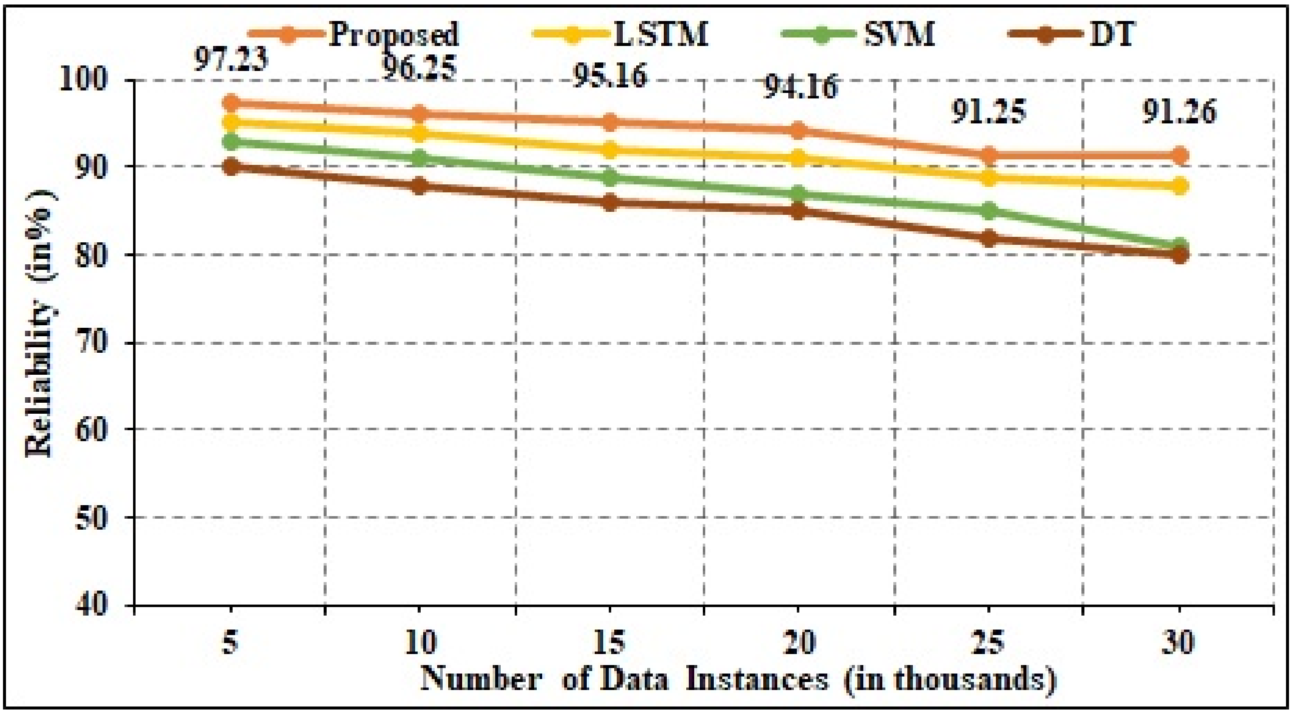


Figure 10: System Reliability

reliability of 80.02%, DT achieved dependability of 72.23%, and SVM achieved average reliability of 64.03%. Based on these findings, it can be concluded that the provided model can outperform other decision-making models in real-time circumstances. As a result, the ANN-based approach suggested is exceedingly efficient and effective.

5 Conclusion

The IoT-inspired forest-fire identification framework for the early determination of wildfires is presented. IoT equipment is initially used to gain powerful features, including temperature, wind intensity, humidity, and precipitation, to ignite wildfires. The key innovation of the proposed methodology is its energy conservation and real-time estimation to take the required steps at an early stage. The data compression technique based on Jaccard Similarity is used for this. The fog-cloud layer then uses compressed data for further analysis. Specifically, characteristics that trigger wildfires are compiled and computed in a Forest Fire Index (FFI). FFI value is utilized in real-time to assess wildfire prediction. Moreover, the ANN model effectively predicts wildfire-prone areas using the Self Ordered Mapping technique for forecast purposes. Numerous laboratory models were conducted to test the proposed method. Several recent detection models were contrasted with the findings. Based on the results, it was inferred that the procedure provided is highly efficient and accurate in wildfire prediction.

One research unlocks new directions for further exploration. There are several applicability domains and technological fields in the modern environment where future research can be done. From the point of view of applicability, these include assessing other hazard consequences such as cyclonic impacts and estimating tidal wave patterns.

Conflict of interest

The authors declare no conflict of interest.

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