ANFIS-Inspired Smart Framework for Education Quality Assessment

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ABSTRACT In the education sector, the Internet of Things (IoT) technology, integrated with fog-cloud computing, has offered productive services. Motivated by this, the smart recommender system offers the facility to the students to opt for the course and college based on the education quality. This research provides an IoT-fog-cloud paradigm for evaluating the academic environment with a perspective to enhance quality education. Specifically, IoT technology is incorporated to gather data about the academic environment that directly and indirectly influence the quality of education. Using the Bayesian Modeling Technique, the data collected is analyzed utilizing a fog-cloud computing framework to quantify the measure of the probability of education quality (PoEQ). Moreover, the Education Quality Assurance Index (EQAI) is calculated to analyze the quality assessment over a temporal scale. Furthermore, predictive decision-making is performed for quality estimation using the Adaptive Neuro-Fuzzy Inference System (ANFIS). The experimental simulation on 4 challenging datasets namely C1 (2124 instances), C2 (2112), C3 (2139), and C4 (2109) shows the effectiveness of the proposed framework. Simulation findings are compared with state-of-the-art techniques to measure the overall performance enhancement of the proposed system. Also, the mathematical analysis was carried out to assess the analytical performance of the proposed framework.

INDEX TERMS Adaptive neuro-fuzzy inference system, smart recommender system, Internet of Things (IoT), fog-cloud computing.

I. INTRODUCTION
Internet of Things (IoT) technology has gained more propulsion with the prevalence and universality of smart devices and sensors [1], [2]. IoT as an emerging technology is used in several fields like Healthcare [3], Transportation [4], Agriculture [5], and Security [6]. Moreover, IoT has played a crucial role in the education sector for providing solutions to improve academic learning, quality of education, campus security, and interaction using IoT devices and sensors. It provides smart solutions to the challenges prevailing in the field of education due to which Smart Recommender System (SRS) is acquiring more popularity. In the education field, SRS plays a crucial role in guiding students in the selection of the best educational institution for higher studies. Recommender systems are commonly used in different domains, and its utility in academic selection can effectively improve student’s performance in the respective field. SRS and academic integrate several IoT sensors, gadgets, and actuators, making the education system more effective. On the other hand, IoT technology backed by intelligent computing paradigms like fog-computing provided a boost to the research innovations [7]. Fog computing, a cloud-addendum platform, provides results in real-time and provides enhanced services to different sectors of the education industry [2], [8].

A. RESEARCH FIELD
Globally, more than 51,534 educational institutions are providing education to the students. On an addendum, there is a significant hike in the number of educational institutions from the past few years. However, rise in the number of educational institutions has degraded the education quality due to which attrition rate is increasing. Every year more than millions of students are enrolled in educational institutions for pursuing higher studies across the world. According to AISHE report

1http://mospi.nic.in/statistical-year-book-india/2017/198
2https://nces.ed.gov/pubs2019/2019144.pdf
in 2018-19, nearly 2,98,29,075 students are enrolled in undergraduate programs, out of which 90,91,898 students passed the course\(^3\). This significant decrease in the percentage of pass out students due to inappropriate student performance assessment systems and an increase in the number of educational institutions around the globe leaves the student in a perplexed state \([9]\). Henceforth, an enhanced solution is indispensable. With the advancement in smart devices and intelligent technologies have originated the requirement for a SRS for retaining students in the institution. Conspicuously, the current research will address the following key aspects:-

1) Academic Institutes are characterized by factors for providing the best education quality to the students. SRS will enhance the student’s performance by providing them a facility to opt for college/university with the best education quality and a healthy environment.

2) Incorporating IoT-Fog-Cloud technology for the development of the SRS framework for education quality assessment for students. Efficacious models are needed to address this issue.

3) Conceptualizing SRS to provide students with the best educational institutes as per their performance.

4) Academic Institutes are not student-centric in terms of education quality perspective.

5) Ranking of academic institutes based on education quality attributes plays a significant role in making decisions effectively and efficiently.

Based on these aspects, analyzing the academic institutes from an educational perspective using IoT-Fog-Cloud technology address the issue of education quality assessment in colleges/universities, and improving the decision-making capabilities of students. IoT technology merged with fog, cloud, and predictive modeling has formed a motivational perspective to carry out the present research.

\(^3\)https://mhrd.gov.in/sites/uploadfiles/mhrd/files/statistics-new/AISHE20Final20Report202018-19.pdf

B. RESEARCH MOTIVATION

IoT-Fog-Cloud and collaboration of the Predictive Modeling (PM) approach provide a novel way of acquiring, processing, and managing ubiquitous data in real-time. PM is utilized for automated decision-making in a smart environment. This article proposes an IoT based automated framework for an education quality assessment of educational institutions. The fundamental concept of the presented framework is to make effective decisions about the education quality and environment of the academics using data acquired by IoT devices. Moreover, with an Adaptive Neuro-Fuzzy Inference System (ANFIS)-based framework, an automated decision-making with enhanced accuracy can be achieved for students and parents to assess education quality of an academic institute. Henceforth, the cognitive decision is formulated by the predictive model in the proposed framework.

C. RESEARCH CONTRIBUTION

The current research presents an efficacious framework for the education-quality based SRS. Figure 1 describes the conceptual framework for the presented recommender system for estimating the quality of education. Specifically, the current research focuses on the following objectives.

1) Incorporating IoT technology to acquire pervasive data of the academic environment in real-time for the quality of education and surroundings of the institute.

2) Analyzing the academic environment for qualitative evaluation in terms of Probability of Education Quality (PoEQ) utilizing the Bayesian Modeling technique.

3) Applying temporal data analysis on IoT-segments using techniques of data mining and performing effective quantification in terms of the Education Quality Assurance Index (EQAI).

4) Formulating Adaptive Neuro-Fuzzy Inference System (ANFIS) based framework for effective decision-making to determine EQAI factor for the education quality-oriented SRS.
5) Validating the proposed model in real-time by assessing the performance enhancement relative to state-of-the-art decision-making techniques.

Moreover, the presented system provides certain beneficial aspects in the field of education monitoring and prediction. Some of the important advantages are as follows:

1) The introduced framework can assess the education quality with the goal that an in-depth analysis can be performed effectively.
2) The proposed framework routinely tracks the education institute for regularized locally situated analysis by the monitoring administrations.
3) Automated performance assessment of the teacher will give compelling academic insight and necessary steps can be taken for improvement.
4) The proposed framework can predict the academic growth of the institute over the temporal scale for provisioning detailed assessment.
5) The incorporation of IoT presents an efficient time-sensitive framework for in-depth analysis by monitoring officials and student guardians.

Paper Organization
Section 2 briefly describes an overview of the related work in the current study. The proposed framework is described in Section 3. The experimental setup and mathematical analysis have been discussed in Section 4. Section 5 concludes the paper with some future research objectives.

II. LITERATURE SURVEY
This section describes some crucial works performed by researchers around the world in the field of smart academic education. In the context of education, Smart frameworks have been efficaciously used for collecting data in real-time. Moreover, the incorporation of ICT technology by researchers in an efficient manner leading to the realization of a smart academic system. In 2019, Mitrofanova et al. [16] have identified numerous techniques for intellectual assessment in the smart education industry. Moreover, several classes have been formulated based on the applications and goals for intelligent education development. Furthermore, numerous beneficial aspects of smart education have been presented for research exploration. In 2019, Assante et al. [17] presented a novel system for the identification of several didactic techniques for incorporating smart technologies in the education sector. Comprehensively, numerous ICT paradigms were considered for the development of the smart education industry including IoT, Cloud Computing, and Artificial Intelligence. In 2019, Lyapina et al. [18] investigated the classical education system in the universities and compared it with the remote assessment procedure using smart ICT technologies. The authors were able to assess the beneficial aspect of smart education technology in terms of data analysis, synthesis, abstraction, and logic. In 2019, Leem et al. [19] analyzed the teacher’s trust for the incorporation of smart medical devices in the education industry. The authors acquired the data instances from nearly 400 primary and secondary teachers for determining the acceptance rate of smart technology in academics. Based on the experimental questionnaire, 5 important factors were identified for the teacher’s belief. These include interactivity, instability, inconvenience, interest, and immediacy. In 2019, Basset et al. [10] proposed an IoT-based supportive framework for smart education. The presented system contributes to making decisions effectively and efficiently regarding the quality of education provided to the students. Moreover, challenges like security, better management, and cost reduction were handled using the presented system. In 2019, Galimullina et al. [11] discussed the use of smart technologies in mathematical education. The authors surveyed teachers and experts to analyze curriculum effectiveness. The results of the study depicted that the use of Smart Education Technologies (SET) motivates the students to handle or solve mathematical problems quickly. In 2018, Verma and Sood [20] developed an IoT-based framework for evaluating the performance of students. The proposed framework generates the results of the student’s performance by analyzing the data collected based on spatial-temporal patterns. In 2017, Gul et al. [21] discussed the role of IoT in education. The authors presented the challenges, impact, and the latest research works in future learning. In 2017, Verma et al. [22] proposed a smart computing framework for evaluating the performance of engineering students. The authors developed 5-layer architecture to generate results by analyzing the performance of students. The results captured by the proposed system were efficient for improving the learning skills of the students in comparison to the results generated by the manual method. In 2016, Zhu et al. [14] provided a research framework for smart education. The authors developed a 4-layer framework with 10 vital features of an intelligent learning environment. The presented framework also discussed the concept of smart education using different techniques. In 2015, Atif et al. [23] proposed a smart system for ubiquitous learning in a smart campus. The proposed method acquired prevalent resources of education that meet the expectations of both teachers and students of a smart campus. In 2017, Bachtiar et al. [24] explores how students learn linguistic skills using adaptive influences. The analysis students are assessed by questionnaires on their cognitive factors, such as motivation, attitude, extraversion, extrusion, fear, and self-esteem. The gathered results were then used to model students with a particular collection of parameters while studying utilizing the Adaptive Neuro-Fuzzy Inference method (ANFIS). In 2020, Bhatia et al. [25] discussed the healthcare industry as the leading area revolutionized by IoT technology that has led to the introduction of intelligent medical applications. The authors have introduced an efficient home-centered urine-based diabetes monitoring system. In 2020, Behal et al. [15] proposed an integrated IoT-based system for tracking and forecasting parameters for air pollution such as benzene utilizing the application of machine learning. The study integrates a methodology to forecast air quality using the Adaptive Neuro-Fuzzy Inference System.
TABLE 1. Comparative analysis with related studies.

| Reference | Fog | IoT | Temporal | Education | Predictive Model | Real-Time | Accuracy | Statistical | Reliability | Stability |
|-----------|-----|-----|----------|-----------|------------------|-----------|----------|-------------|-------------|-----------|
| 10        | ✗   | ✓   | ✓        | ✓         | ✗                | ✗         | ✓        | ✗           | ✗           | ✗         |
| 11        | ✗   | ✗   | ✗        | ✓         | ✗                | ✓         | ✗        | ✓           | ✗           | ✗         |
| 12        | ✗   | ✓   | ✗        | ✓         | ✓                | ✗         | ✗        | ✗           | ✗           | ✗         |
| 13        | ✓   | ✗   | ✓        | ✓         | ✓                | ✓         | ✗        | ✗           | ✗           | ✗         |
| 14        | ✓   | ✗   | ✓        | ✓         | ✓                | ✓         | ✗        | ✗           | ✗           | ✗         |
| 15        | ✓   | ✓   | ✓        | ✓         | ✓                | ✓         | ✗        | ✗           | ✗           | ✗         |
| Proposed  | ✓   | ✓   | ✓        | ✓         | ✓                | ✓         | ✓        | ✓           | ✓           | ✓         |

(ANFIS). In 2019, Kaur and Sood [26] proposed a framework for diluting damage caused by wildfires utilizing ANFIS, which provides an effective real-time approach. In 2020, Manocha et al. [27] have proposed a 2-phase decision-making process by utilizing ANFIS which further helps to optimize transmission by evaluating the vulnerability scale of the medical services needed. Based on the comprehensive literature review, Table 1 shows the comparative analysis of the proposed model with state-of-the-art related studies in the current domain.

III. PROPOSED MODEL

Figure 2 presents the proposed IoT-based framework of the SRS for analyzing the quality of education in a specific academic institute. The presented framework comprises of 4 layers, namely Data Acquisition and Pre-processing (DAP), Data Classification (DC), Data Mining (DM), and ANFIS-based Predictive Decision-Modeling (APDM) layers. Each layer performs specific functions to attain certain objectives. Initially, data is captured from several IoT devices embedded in the ambient environment of the academic. Data captured is sent to fog-computing devices for determining the education quality of the institution. Finally, detailed information is transmitted to the cloud for decision-modeling based on the education quality scale. The functionality of each layer is discussed ahead in detail.

A. DATA ACQUISITION AND PRE-PROCESSING (DAP)

DAP is the initial layer of the proposed framework of the education quality-oriented SRS. The purpose of this layer is to collect data about the academic environment, education quality, and staff activities. For this reason, several IoT
TABLE 2. Data set classification and feature capturing mechanism.

| Class                      | Sub-Class          | Explanation                                                                 | Feature Extraction  | IoT Technology Utilized | Parametric Value |
|----------------------------|--------------------|------------------------------------------------------------------------------|---------------------|-------------------------|------------------|
| Environmental Dataset      | Cleanliness        | It depicts the cleanliness of the surroundings.                             | Stochastic Signal   | Dust Sensor             | Qualitative      |
|                            | Noise              | It describes the noise level of the area where college/university is located. | Static Signal       | Noise Sensor            | Quantitative     |
|                            | Infrastructure     | It represents the cleanliness of the furniture as well as the lighting condition of the classrooms. | Static Signal       | Dust Sensor and Light Sensor | Quantitative     |
| Staff-related Dataset      | Behavior           | It describes the teacher’s behavior towards students.                      | Stochastic Signal   | Body Sensor             | Qualitative      |
|                            | Punctuality        | Regularity of a teacher for coming to the class                           | Dynamic Signal      | Clock Sensor            | Quantitative     |
|                            | Student Satisfaction | It tells the satisfaction of a student towards the lecture delivered by the teacher. | Dynamic Signal      | Feedback Perform        | Quantitative     |
| Physical Dataset           | Location           | It describes the information regarding the location of the academic.       | Static Signal       | Static Data             | Quantitative     |
|                            | Distance           | It represents the distance of a academic from a particular place           | Static Signal       | Static Data             | Quantitative     |
|                            | Working Hours      | It describes the working hours of the academic.                            | Static Signal       | Static Data             | Quantitative     |
| Student Academic History-related Data | Academic Performance | It tells the previous record of the student’s performance.              | Static Signal       | Static Data             | Quantitative     |
|                            | Punctuality        | Regularity of student in the class                                         | Static Signal       | Clock Sensor            | Quantitative     |

FIGURE 3. Data processing and categorization.

devices such as Wireless sensors, Radio Frequency Identifiers (RFID), GPS sensors, and actuators are displaced within the academic’s ambient environment. Data acquired is transmitted to the fog node for an alert generation regarding the education quality of a specific academic environment. This data is transmitted utilizing different communicating protocols namely Wi-fi, Bluetooth, and Ethernet [28], [29]. Data from fog node is sent to the cloud repository for precise analysis by the users. Data transmission protection to the cloud is maintained using Secure Socket Layer (SSL) [30]. Also, fog-cloud-level data is secured using protocols such as Credential Mapping and User Authentication [31]. Data pre-processing incorporates th data cleaning of the noisy data or missing data acquired from the IoT devices. In the presented study data cleaning is realized using Kalman filters for maximal accuracy.

B. DATA CLASSIFICATION (DC): FOG LEVEL
Data acquired from IoT devices and sensors are directly and indirectly related to education quality. Henceforth, it is necessary to quantify these parameters before an in-depth analysis of specific data sets. Also, multiple extractions and
pre-processing mechanisms need to be implemented to improve the accuracy of the proposed model. In Table 2 some of the important features of education quality have been listed. In this research, based on the education quality assessment, 4 categories of datasets have been presented. These are Environmental Datasets (ED), Staff-Related Dataset (SD), Physical Dataset (PD), and Students Academic-related Historic Dataset (SAHD).

1) Environmental Dataset (ED):- ED consists of the data values which are related to the ambient environment of the academic institute. These include cleanliness, noise, infrastructure, and classrooms. Data is acquired using IoT sensors and devices displaced inside the academic environment.

2) Staff-related Dataset (SD):- It is another important dataset that plays a significant role in the education quality assessment. SD dataset includes the data about the faculty recruited in the academic. The main attributes that are considered for faculty are communication skills, punctuality, student satisfaction, and their behavior towards the students. The quality of education immensely depends on the teaching methods adopted by the teachers.

3) Physical Dataset (PD):- PD datasets are confined to the attribute values like the location of a academic institute, distance from the particular place, and study hours.

4) Student Academic History-related Dataset (SAHD):- SAHD dataset comprises of the historical record of the student’s performance. The student’s performance history is retrieved from the cloud storage repository.

1) DATASET CLASSIFICATION
As mentioned earlier, the main focus of the DC layer is to classify the datasets acquired by the Data Acquisition layer. In the presented framework, the dataset classification is carried out based on the probabilistic metric termed as Probability of Education Quality (PoEQ).

Definition 1: Probability of Education Quality (PoEQ): Let a data sequence is given by $D_t$ for time instance $T_t$, PoEQ is defined as the probabilistic impact (positive and negative) of $D_t$ on the education quality for the corresponding time instance.

The above definition gives us the probabilistic measure for analyzing the effect of the particular parameter on education over a quality scale. Based on the PoEQ, 2 classes are described utilizing the Bayesian Belief Network (BBN) model [32], [33] in the form of Implicit Class (IC) and Explicit Class (EC) as depicted in Figure 3.

1) Implicit Class (IC):- This category has a direct impact on the education quality. In other words, it is characterized by the factors that have a direct impact on the education quality like behavior of a teacher, regularity, teaching ability, infrastructure cleanliness, and noise.

2) Explicit Class (EC):- The class of dataset comprises of those activities that are indirectly related to the education quality of a specific academic. In other words, it comprises those data instances that dont have any major effect on the academic’s reputation in terms of education quality perspective. The physical data values like location, distance, timings are some of the examples of an explicit class dataset.

2) MATHEMATICAL ANALYSIS
Let $\rho(S_T/E)$ and $\rho(S_E/E)$ represents both “True” and “False” probability values the academic parameter $P > \lambda$ (predefined threshold) at time $\delta t$ for timeslot $Q_i$ ($Q_i \leq Q_1, Q_2, Q_3$), and $\omega$ be the corresponding weight for parameter E. The Bayesian model determines the prior probability $\rho_{0}(E > \lambda/S_T)$ as follows:

$$\rho_{0}(E/S_T) = \rho(E) * \rho(S_T/E)$$

**Probabilistic Categorization:**

Posterior probability $\rho_{o}(S_T/E)$ is a probability function with associated weight as $\rho_{0}(E/S_T)$. Henceforth, $\rho_{o}(S_T/E)$ can be inferred as follows:

$$\rightarrow \rho_{\delta o}(S_T/E) = \rho_{0}(E/S_Q) * \rho(S_T/E)$$

$$\rightarrow \rho_{\delta o}(S_T/E) = \omega(E)*\rho(E/S_T)*\rho(S_T/E)$$

where, $\rho(E) = \rho_{0}(E/S_T)\rho(S_T) + \rho(E/S_E)\rho(S_E)$

Moreover, $\rho_{0}(E/S_T)$ is a probability function of $E$ for given a time window $\delta t$, PoEQ ($\rho_{0}(E)$) measure is estimated as:

$$\rightarrow \rho_{0}(E) = \omega_{0}(E)\rho(E/S_Q) + \rho(E/S_E)\rho(S_E)$$

After assessing $n$ academic parameters for a given a time window $\delta t$, PoEQ ($\rho_{0}(E)$) measure is estimated as:

$$\rightarrow \rho_{0}(E) = \frac{1}{n} \sum_{E} \rho_{\delta o}(S_T/E)$$

$$\rightarrow \rho_{0}(E) = \omega_{0}(E)\rho(E/S_Q) + \rho(E/S_E)\rho(S_E)$$

3) NUMERICAL ILLUSTRATION

This section describes exemplary analysis to depict the incorporation of Bayesian technique for assessing the academic quality feature. 3 education-related teacher features including teaching-delivery, regularity, and task-completion are considered. Moreover, all these parameters are measured in terms of probability i.e between (0,1). Based on these parameters, the presented model will estimate the PoEQ value for detailed assessment. Initially, these parameters are acquired by IoT sensors embedded in the ambient infrastructure of class and institute. Assume, the probabilistic values of the teaching delivery parameter to be greater than threshold is 1, 0 for regularity, and 1 for task-completion. Then, the corresponding weight can be estimated as:

$$\omega(“teaching-delivery”') = \frac{1}{0+1} * \frac{1}{0+1} + \frac{1}{1+1} * \frac{0}{1+1} = 67%$$

$$\omega(“regularity”') = \frac{1}{0+1} * \frac{1}{0+1} + \frac{1}{1+1} * \frac{1}{1+1} = 33%$$

$$\omega(“task-completion”') = \frac{1}{0+1} * \frac{1}{0+1} + \frac{1}{1+1} * \frac{1}{1+1} = 33%$$

Assuming that threshold of teaching-delivery is 0.53, 0.63 for regularity and 0.71 for task-completion. Posterior
probabilities are estimated as
\[
\rho(PoEQ(Quality)/teaching-dummy) = 0.67 \times 0.3 \times 0.2 = 0.137
\]
\[
\rho(PoEQ(Quality)/regularity) = 0.33 \times 0.2 \times 0.33 = 0.043
\]
\[
\rho(PoEQ(Quality)/task-completion) = 0.33 \times 0.18 \times 0.67 = 0.035
\]

It can be seen that \(\rho(PoEQ(Quality)/teaching-dummy) = 0.71\) which is greater than then other parameters. Consequently, the total PoEQ for \(\delta t\) time window is evaluated as
\[
\text{Avg.}(PoEQ_{\delta t}) = \frac{1}{3}[0.71 + 0.43 + 0.51] = 0.55
\]

C. DATA MINING (DM)

Data Mining (DM) Layer is the third layer of the proposed framework for assessing the education quality of a specific academic. The key concept of this layer is to acquire the data values from the repository for IC and EC datasets. Moreover, one of the crucial tasks carried out by the DM layer is to critically map every education quality parameter with the temporal aspect for effective real-time assessment. For the purpose described above, the temporal mining technique has been utilized. It is a data extraction method for time-based evaluation of the data values [34]. Also, this article proposes a technique of temporal granulation to extract parameters of education quality within a given time.

1) FORMULATING TEMPORAL MINING

It is an approach for data abstraction for specific parameters and aggregating them over temporal scale. Representing Temporal Mining formally as:
\[
< D_1, T_1 >, < D_2, T_2 >, \ldots, < D_n, T_n >,
\]
where \(D_i\) depicts the value of \(i^{th}\) parameter at given time instance \(T_i\). For synchronization, several data values are accumulated. In addition, such uniformity enables education quality to be extracted from a common temporal platform. It will effectively help to quantify education quality. The analysis of education quality parameters in the proposed model is defined in terms of the probabilistic measure of the EQAI.

Definition 2: Education Quality Assurance Index (EQAI): It is described as the quantification measure of education quality over temporal granulation \(< D_1, T_1 >, < D_2, T_2 >, \ldots, < D_n, T_n >\) in a specified time instance \(T\).

The definition stated above combines a numerically unified value with the heterogeneous education quality parameters captured by IoT devices utilizing the PoEQ parameter. The higher the value of the EQAI parameter, the better the education quality registered for the educational institution. Similarly, low EQAI is a sign of poor education quality delivered by a college/university. Current work uses Map-Reduce functions to achieve parallelism [35]. These are programming paradigms for distributed computing processes. Tools such as Apache Hadoop and Spark are commercially capable of extracting and processing parallel data in real-time. On the basis of quantification, the EQAI can be evaluated using Algorithm 1 (Table 3). It sets out a brief procedural step for quantifying the EQAI. Initially, a comparison of parameter values is made with the threshold values predefined by the parents and the management authorities. In addition, it is developed to add values*PoEQ to the EQAI if a parameter value is greater than the threshold, otherwise 0 is added. Similarly, steps are repeated to estimate the overall education quality. The result is averaged over number of parameters utilized. This is an important technique for aggregating multiple segments of data. On the basis of this procedure, the maximum and minimum values are within the range of (0,1) where 0 indicates poor education quality and 1 shows better education quality.

D. PREDICTIVE DECISION MAKING (PDM) LAYER

Adaptive Neuro-Fuzzy Inference System (ANFIS) is used by numerous researchers in several fields for predictive decision-modeling [36]. In general, ANFIS [37] is used to resolve highly complex and non-linear problems. The 5-layer ANFIS framework with four inputs is shown in Figure 4. The Fuzzy Logic provides multi-value logic input from the single parental input variable representing the single value set relationship with set of other values [38]. A fuzzy inference model is used in the proposed framework to non-linearly map vectors input. In the current research, each education quality parameter is assessed by the proposed ANFIS model within a given space-time window. For instance, the data values for assessing the quality of education in the academic environment in a specific time-space window is fed to the ANFIS for which its predictability value is calculated. The detailed mathematical analysis of ANFIS layers is addressed ahead.

1) FUZZIFICATION (LAYER 1)

The first layer of the ANFIS model is fuzzy layer, which transforms the inputs to a fuzzy set by utilizing membership functions (MFs). Each node in this layer is adaptive in nature and is shown as:
\[
M^1_j = \mu_G(w)
\]
where \(M^1_j\) is the Gaussian membership function, \(w\) is assumed as the input value given to the node \(j\), and \(G_j\) is assumed as the linguistic attribute which that has been associated to a node function [39]. In the current context, the initial fuzzification layer is actually provided with spatio-temporal data values for various education quality parameter instances.

2) PRODUCT RULE (LAYER 2)

By conducting the element-wise product operation, the nodes of the second layer pass the input signal to the next layer and is represented mathematically as follows:
\[
M^2_j = \mu Z_j(w) \times \mu A_j(x), \quad j = 1, 2
\]
where \(Z_j(w)\) and \(A_j(x)\) represents the nodes in layer 2.
TABLE 3. Education quality assurance index (EQAI) measure procedure.

| Step | Description |
|------|-------------|
| 1    | Input IoT data values for m parameters and associated PoEQ values. \( \theta \), \( \delta \), \( \beta \), and \( \gamma \) are the corresponding values. |
| 2    | Initialize EQAI at specific time instance=0. |
| 3    | PoEQ value of m parameters is compared with prefixed threshold variable \( \alpha \) i.e. set by the parents based on the academic score and capability of their ward. |
| 4    | If value of PoEQ1 > \( \alpha_1 \), then add \( \theta \times \text{PoEQ1} \) to EQAI. |
| 5    | If value of PoEQ2 > \( \alpha_2 \), then add \( \delta \times \text{PoEQ2} \) to EQAI. |
| 6    | Repeat the steps for m parameters. |
| 7    | If value of PoEQn > \( \alpha_n \), then add \( \gamma \times \text{PoEQn} \) to EQAI. |
| 8    | Cumulative EQAI = \( \frac{1}{n}(\theta \times \text{PoEQ1} + \delta \times \text{PoEQ2} + \beta \times \text{PoEQ3} + ... + \gamma \times \text{PoEQn}) \). |

FIGURE 4. Structure of ANFIS.

3) NORMALIZATION (LAYER 3)
The ratio of the single firing strength rule to the sum of any firing strength rules represented in Equation 3 is calculated by each node of that layer. The firing strength is denoted by \( v'_j \) and is further standardized as follows:

\[
M^3_j = v'_j \frac{v_j}{v_1 + v_2} \quad \text{for } j = 1, 2 \quad (3)
\]

4) DE-FUZZIFICATION (LAYER 4)
This layer has the responsibility for assessing the contribution to the final output of the \( j^{th} \) rule. The corresponding structured consequent variables are classified as the \( b_i \), \( c_i \) and \( q_j \) parameters. The de-fuzzification function in this layer is as follows:

\[
M^4_j = v'_jf_j = v'_j(b_jw + c_jx + q_j) \quad \text{for } j = 1, 2, \ldots, n. \quad (4)
\]

5) OUTPUT GENERATION (LAYER 5)
It is regarded as an output layer, which calculates the total of all outputs from all de-fuzzification nodes and calculates the final value. \( M^5_j \) as denoted in Equation (5):

\[
M^5_j = \sum v'_jf_j = \frac{\sum_j v'_jf_j}{\sum_j v_j} \quad (5)
\]

E. INSTITUTIONAL QUALITY ASSESSMENT INDEX (IQAI)
IQAI presents a novel quality assessment index for assigning ratings to the institute. Specifically, it comprises of 3 important factors including, Education Quality, Environmental Factors (Environmental Feasibility Index (EFI)), and Socio-Economics Aspect (SEA). All these parameters are important.
FIGURE 5. Temporal delay efficiency.

to assess the particular instate for an in-depth analysis of the academic environment conspicuously, the IQAI can be estimated as:

\[ IQAI = \alpha \ast EQAI + \beta \ast EFI + \gamma \ast SEA \]

where \( \alpha \) indicates the associate weight for the predicted EQAI value, \( \beta \) depicts the weight for static Environmental Feasibility Index, and \( \gamma \) is associated weight for socio-economic aspect. These static measures and associated weights are estimated by domain expert for enhanced assessment.

IV. EXPERIMENTAL EVALUATION

The presented approach of IoT-Fog inspired smart education quality prediction system consists of crucial steps. Initially, academic-based parameters are captured in real-time using several IoT devices utilized in the ambient academic environment. The data acquired is transmitted to fog node which acts as the interface for communicating data to the cloud. Based on the data stored at the cloud, predictive model is formulated for effective decision-making based on EQAI value. With this measure, appropriate ranking of academics is provided. Conspicuously, the proposed model analysis is based on 4 performance parameters. These are:

1) Determining the efficiency of capturing data using IoT devices in terms of temporal delay.

2) Evaluate the classification efficacy of the presented model in comparison to state-of-the-art models.

3) Estimating the prediction efficiency of the proposed framework for evaluating the education-based implicit and explicit data segments.

4) Analyzing the reliability and stability of the presented system for 4 different datasets.

5) For achieving the overall accuracy mathematical analysis of the presented framework is analyzed.

A. SIMULATION ENVIRONMENT

The proposed model simulation was carried out in real-time on 4 datasets namely, C1, C2, C3, and C4 mapped over the time-period of 50-day. Cumulatively, 8448 values were acquired from all datasets to estimate the performance enhancement of the proposed system. It includes 2124 instances from C1, 2112 from C2, 2139 from C3, and 2109 from C4. Moreover, these datasets include activities like behavior, student satisfaction, noise, cleanliness, and punctuality as described in Table 2. Raspberry Pi v3 is utilized as a fog computing node. Moreover, data classification is implemented utilizing Bayesian classifier of the WEKA
open-source toolkit. The experimental simulation was carried out on the computer system having RAM of 16 GB, Processor Intel Core i5, and 3.2 GHz clock cycle.

### B. TEMPORAL DELAY

Temporal Delay is defined as the time required to formulate predictive decisions. In other words, it is described as the time needed for assessing data repository and result generation. If $T_{IoT-Monitoring}$ denotes the time required by IoT devices for assessing data, $T_{Data-categorization}$ depicts the time for categorizing the data, and $T_{Decision-modeling}$ is the time needed for formulating the decision, then the temporal delay is estimated as follows:

$$\text{Temporal Delay} = T_{IoT-Monitoring} + T_{Data-categorization} + T_{Decision-modeling}.$$  

1) Figure 5(a) depicts the results for temporal efficiency for C1 Dataset. It shows that the IoT model proposed can acquire data in 23.03 seconds on average. Similarly, for data classification time required is 25.68 seconds. In addition, the time taken by the current model for decision-making is 26.66 seconds, resulting in an overall average delay of 75.37 seconds.

2) Figure 5(b) shows that the average temporal delay for C2 Dataset. The graphical construct depicts that approximately 24.26 seconds are incorporated by IoT monitoring. The time registered for data classification is 24.56 seconds. Moreover, 26.70 seconds are register for predictive decision-making. Overall running time was averaged to 75.72 seconds.

3) Figure 5(c) describes that the overall execution time for the presented framework is 76.97 seconds for C3 Dataset. This delay entails 24.98 seconds for data acquisition, 25.78 seconds for data classification and 26.21 seconds for predictive decision-making. Overall running time was averaged to 76.98 seconds.

4) Figure 5(d) depicts the temporal efficacy for C4 Dataset. Similarly, the overall execution delay of 76.26 seconds was reported for the presented model. Based on the results generated, it is seen that the presented procedure registers a minimum delay in overall decision-making.

### C. CLASSIFICATION EFFICIENCY

The performance of the presented model is estimated for classification proposes in terms of Precision (Pc), Specificity (Sp), and Sensitivity (Ss). For comparative analysis, 2 state-of-the-art classification mechanisms have been used including Decision Tree (DT), and Support Vector Machine (SVM). It is noteworthy to mention that during simulation only the classification model is altered while the remaining model is kept identical. Moreover, only average results are depicted for better assessment. Table 4 depicts the detailed analysis of the acquired results. As mentioned earlier, the classification is deployed over the WEKA toolkit.

- a) It can be seen that during implementation the presented model can acquire an enhanced precision measure of 95.59% in comparison to 90.12% for DT and 91.25% for SVM. Henceforth, the presented model of BBN is more precise as compared to other classifiers.

- b) For specificity estimation, the presented system acquires a value of 94.55% in contrast to DT (90.12%), and SVM (92.52%). It depicts the effectiveness of the presented model.

- c) For sensitivity analysis, it can be seen that the proposed approach is more efficient as compared to other techniques by registering a value of 93.65%. In comparison to this, SVM obtained a value 91.6% and DT attained 90.14% value.

Henceforth, based on the results, it can be concluded that the presented system is more effective in the classification of datasets as compared to other state-of-the-art models.

### D. PREDICTION EFFICIENCY

The estimated outcomes for the assessment of prediction output are described in the Table 5, and Table 6 using the state-of-the-art decision methods on the different datasets. In particular, it demonstrates the association between

| Dataset | BBM Classifier | Decision Tree | Support Vector Machine |
|---------|----------------|---------------|------------------------|
| 800     | 92.25          | 92.22         | 92.22                  |
| 1600    | 94.48          | 91.12         | 91.12                  |
| 2400    | 95.57          | 93.32         | 93.32                  |
| 3200    | 92.15          | 94.42         | 94.42                  |
| 4000    | 93.46          | 91.81         | 91.81                  |
| 4800    | 94.62          | 92.21         | 92.21                  |
| 5600    | 95.32          | 91.13         | 91.13                  |
| 6400    | 94.42          | 91.22         | 91.22                  |
| 7200    | 91.12          | 90.04         | 90.04                  |
| 8000    | 95.59          | 90.12         | 90.12                  |

| Model   | BBM Classifier | Decision Tree | Support Vector Machine |
|---------|----------------|---------------|------------------------|
| Dataset | Pc(%)          | Sp(%)         | Ss(%)                  |
| 800     | 92.25          | 92.24         | 92.22                  |
| 1600    | 94.48          | 93.92         | 93.22                  |
| 2400    | 95.57          | 92.84         | 94.42                  |
| 3200    | 92.15          | 92.94         | 93.32                  |
| 4000    | 93.46          | 92.72         | 91.14                  |
| 4800    | 94.62          | 92.82         | 90.12                  |
| 5600    | 95.32          | 92.33         | 93.41                  |
| 6400    | 94.42          | 93.33         | 92.22                  |
| 7200    | 91.12          | 92.20         | 92.42                  |
| 8000    | 95.59          | 94.55         | 93.65                  |

| Model   | BBM Classifier | Decision Tree | Support Vector Machine |
|---------|----------------|---------------|------------------------|
| Dataset | Pc(%)          | Sp(%)         | Ss(%)                  |
| 800     | 92.25          | 92.24         | 92.22                  |
| 1600    | 94.48          | 93.92         | 93.22                  |
| 2400    | 95.57          | 92.84         | 94.42                  |
| 3200    | 92.15          | 92.94         | 93.32                  |
| 4000    | 93.46          | 92.72         | 91.14                  |
| 4800    | 94.62          | 92.82         | 90.12                  |
| 5600    | 95.32          | 92.33         | 93.41                  |
| 6400    | 94.42          | 93.33         | 92.22                  |
| 7200    | 91.12          | 92.20         | 92.42                  |
| 8000    | 95.59          | 94.55         | 93.65                  |
the parameters in terms of Accuracy, and Root Mean Square Error (RMSE) values reported while testing on the datasets. Numerous prediction frameworks including K-Nearest Neighbor (K-NNR), Support Vector Machine (SVR), Artificial Neural Network (ANN), and Stochastic Gradient Descent (SGD) model and Decision Tree Regression (DTR) have been implemented for comparative study. In addition, several ensemble techniques were used for comparative analysis, such as Random Forest, Adaptive Boosting (AdaBOOST), Gradient Boosted Decision Trees (GBDT). It should be noted that only the prediction function is changed during implementation while the rest of the model is remained unchanged. Detailed results are listed ahead.

1) The accuracy value for the presented prediction strategy is shown in Table 5. This indicates that in contrast with other baseline and ensemble approaches in the prediction process with marginal modifications to the C1 dataset, the proposed approach has obtained an improvement in accuracy of 98.3%. Likewise, the proposed model has been able to record the 98.6% accuracy value, which is comparatively better than other techniques for the C2 dataset. The presented technique was also able to exceed the performance of other techniques and recorded accuracy of 98.8% and 98.7% for C3 and C4 data sets, respectively.

2) The Root Mean Square Error (RMSE) findings are seen in Table 6. For the prediction values of the proposed model, RMSE is an important measure of error determination. Mathematically,

$$RMSE = \sqrt{\frac{1}{m} \sum_{j=1}^{n} \left( \frac{x_j - y_j}{\zeta_j} \right)^2},$$

where $\zeta_j$ denotes the error that was obtained from the model training for the instance of $j^{th}$ and $m$ indicates the number of instances. The proposed methodology is seen to achieve a reduction in RMSE (2.6%) for C1, which demonstrates further that the model’s predictive accuracy. In comparison, the RMSE was reported with a minimum rating of (1.9%, 1.5%, and 1.8% respectively) relative to other ensemble and baseline models for C2, C3, and C4. Moreover, it can be concluded that the proposed approach for estimating education quality in real-time is comparatively better and accurate.

E. RELIABILITY ANALYSIS

It is a crucial aspect of accessing the overall performance of the presented framework. For determining the reliability of the proposed model, results are compared with state-of-the-art prediction models. The change in reliability trends of the prediction models determines its accuracy level. With the increase in the number of data instances for experimental simulation, the reliability is maximized. The results of the simulation are described in Figure 6. From this, it is concluded that the model presented has the highest value of reliability, i.e., 94.87% in comparison to K-NN(90.26%), ANN(92.46%), and SVM(93.16%). Furthermore, the consistent higher trend of the proposed predictive decision-making makes it an efficient method for the decision-making of the education quality of the particular academic institute.

F. STABILITY ANALYSIS

It describes the stability of the presented framework over data instances. The stability of a system is measured in terms of Mean Absolute Shift (MAS). The MAS value ranges from 0 to 1, where 0 denotes the minimum system stability, and
I denotes the system with maximum stability. The outcomes are depicted in Figure 7. It can be seen that MAS has a minimum value of 0.44 and a maximum value of 0.78, averaging to 0.70. Henceforth, it can be inferred that the IoT-based proposed model for analyzing the education quality is very effective and efficient.

V. CONCLUSION

In this article, a smart framework has been developed to analyze the education quality of the academic institute utilizing the IoT-Fog-Cloud paradigm. IoT data values acquired from academic monitoring are expressed in terms of quantifiable parameters of the Probability of Education Quality (PoEQ) and Education Quality Assurance Index (EQAI). Based on these measures, the Adaptive Neuro-Fuzzy Inference System (ANFIS)-based prediction model is presented to determine the education quality by the academics. The simulation evaluation optimized the applicability of the presented system. The validation of the presented model was carried out on 4 challenging datasets with approximately 8,000 data instances. From the results, the model presented is shown to be very effective and reliable in accurately accessing the education-quality in comparison to the state-of-the-art decision-making models. Therefore, it is concluded that the proposed framework is immensely effective and efficient in presenting an education-oriented SRS. For the futuristic aspect, the presented model can be further conceptualized for the academic ranking across the globe. Moreover, software solutions can be derived for the students for accessing the quality of education in a time-sensitive manner.

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