Cognitive Framework of Food Quality Assessment in IoT-inspired Smart Restaurants

Munish Bhatia and Ankush Manocha

***Abstract*—Information and Communication Technology (ICT) empowered by the Internet of Things (IoT), and fog-cloud paradigm has been widely adopted in several domains of logistics, healthcare, and agriculture. Inspired by the enormous benefits of IoT technology, this research proposes a novel notion of smart restaurants for assessing the food quality using game theory. Specifically, this research presents a smart framework for food quality assessment inside restaurants. Real-time data is acquired using numerous IoT devices for food quality assessment. The data is communicated to the fog nodes backed by the cloud platform. This enables the time-sensitive analysis of food quality for formalizing a quantifiable measure i.e. Food Quality Estimate (FQE) using Bayesian Modeling Technique. FQE presents a quantification factor for assessing food quality over temporal patterns in terms of the Quality Support Index (QSI). This is followed by the 2-player game model for effective food quality assessment. The presented model is validated by deploying it over 4 data sets. Based on the comparative analysis with other decision-making techniques, the presented technique has registered superior performance in terms of temporal effectiveness, classification efficacy, statistical efficiency, and reliability.**

Keywords*—*Smart Restaurant, Fog-Cloud Computing, Game Theory, Decision-Making

I. INTRODUCTION

Internet of Things (IoT) has been the pivotal driver for innovations in smart environments like Healthcare, Logistics, and Agriculture, leading to Industry 4.0[1]. With the developments carried out by this revolutionary paradigm, the technological growth of the world is directed towards advance research and innovations[2]. Fog computing, an extension of the cloud computing platform, aims at empowering IoT technology to generate novel solutions for the complex time-sensitive problems by performing data analysis at the network edge[3]. In the food industry, the integration of IoT, Fog and Cloud computing have uncovered numerous services provisioning applications[4]. The prominence focus on food technology has led to the development of futuristic novel solutions for provisioning effective food-oriented services.

Globally, more than 15 million restaurants are provisioning food services to people[1]. On an addendum, street vendors, food chains, and home-based food supply services are countless around the world. The enormous growth rate of the food industry has led to the eminent focus on the diseases and health vulnerabilities caused by the adverse food quality[5][6]. In fact, poor food quality, inappropriate food environments, and adverse preservatives are some of the main causing factors for the widespread food-oriented diseases[7]. According to the report by the World Health Organization (WHO), each year 600 million cases of foodborne diseases are registered globally, out of which 420,000 results in deaths[2]. According to WHO estimation, 33 million healthy lives have been lost due to improper food quality around the world. Food-oriented diseases include stomach cramps, nausea, vomiting, food poisoning, and cancer. The factors identified for such vulnerability are specified as poor food-quality, dirty environment, utilization of expired food products, and contamination at the food preparation centers. Conspicuously, some of the major aspects focused in the current research include (a) Food restaurant and hubs are identified by provisioning poor food quality to the consumers. Mechanisms and techniques must be designed to address this concern; (b) Inappropriate government procedures have failed to deliver effective food quality to the people, leading the financial burden. Cost-effective solutions are desirable for effective deployment; (c) The consumer-centric approach of food hubs and restaurants are the need-of-the-hour for the current food industry; (d) Efficient fog-cloud based IoT technology has the potential to enable enhanced decisive services for consumers, users and quality assessment organizations; (e) Real-time data analysis is crucial parameter for decision-making in food quality perspective. The trio-conceptual notion of IoT, fog, and cloud computing present an effective framework for data acquisition, processing, analysis, and decision-making in a time-sensitive manner. Data acquisition from restaurants, food-hubs, and eating points in the form of both microscopic and macroscopic data segments formulate the underneath core of the proposed research. Additionally, with the development of advance data analysis techniques like deep and machine learning, the conceptual framework of the smart food environment can be acquired with high efficacy. Moreover, the incorporation of game-theoretic decision modeling has further

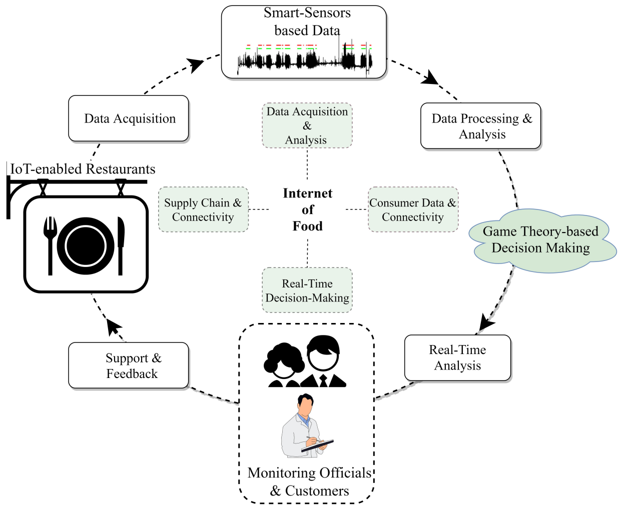

Fig. 1. Conceptual Framework of Smart Restaurant Environment

M. Bhatia is with the Department of Computer Science and Engineering, Lovely Professional University, Punjab, India E-mail: munishbhatia90@gmail.com.

A.Manocha is with the Department of Computer Applications, Lovely Professional University, Punjab, India E-mail: ankushmanocha31@gmail.com

[1]Source:https://thewebminer.com/

[2]Source:https://www.who.int/activities/estimating-the-burden-of-foodborne-diseases

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TABLE I. COMPARATIVE ANALYSIS

Reference	Fog	IoT	Time Analysis	Food Quality	Game Theory	Customer centric	Time Sensitivity	Accuracy	Performance	Reliability	Security
[8]	No	No	Yes	Yes	Yes	Yes	No	No	No	No	No
[9]	No	Yes	No	Yes	No	No	Yes	Yes	No	No	No
[10]	No	Yes	No	Yes	No	Yes	Yes	Yes	No	No	No
[11]	No	Yes	No	Yes	No	No	Yes	Yes	No	No	Yes
[12]	No	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	No
[13]	No	No	No	No	Yes	Yes	Yes	Yes	Yes	No	No
[14]	No	No	No	Yes	No	Yes	No	No	Yes	No	No
Proposed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

enhanced the accuracy level for both consumers as well as the resultant owners to meet specific food quality standards. *Novel contributions* presented in the current research are (a) Perceiving ubiquitous food-oriented data using IoT technology for food quality assessment over the fog-cloud platform; (b) Performing effective data categorization based on the quantifiable measure of Food Quality Estimate (FQE) over fog computing nodes (smart routers); (c) Analyzing data segments over the temporal scale to determine an efficient prevalence measure of Quality Support Index (QSI) for minimizing delay over fog computing platform; (d) Proposing an efficient 2-player game-theoretic decision-model for estimating the food quality using cloud computing; (e) Validating the presented approach over several challenging data sets for estimating the performance enhancement as compared to state-of-the-art decision-mechanisms. Figure 1 shows the ideology of the smart food environment.

Paper Organization: Section II discusses a brief review of related studies in the current domain. The proposed framework is depicted in Section III. Section IV presents the experimental simulation of the proposed model of smart food quality assessment. Finally, Section V concludes the paper with future research directions.

II. LITERATURE REVIEW

This section provides a brief review of the IoT-Fog-Cloud based food quality assessment frameworks developed by researchers around the world. In 2020, Alfian el al. [11] proposed a study to track and trace perishable food by utilizing IoT sensors. Moreover, numerous sensors were incorporated to measure the level of temperature during storage and transportation concerning the scale of humidity. However, the presented study has limited application to the restaurant environment for assessing food quality. In 2020, Lau et al. [12] proposed a novel mechanism of game-theoretic decision-modeling for organic food authentication problems. Authors have incorporated the concept of fines and penalties to the dishonest suppliers and bonus to integral suppliers. In 2020, Lee et al. [13] proposed an agent-based model for the Agriculture 4.0 industry to improve the cultivation of rice by the farmers. Specifically, the presented mechanism incorporates 2 types of farmer effort including cultivation effort and facility maintenance effort. The evolutionary game model has been presented to provide better decision-making over the effort implication problem. In 2019, Asian et al. [8] presented a novel algorithm for organic food supply chain supply systems to maximize financial gains with higher sustainable development. Moreover, the generated profits are distributed among suppliers using cooperative game theory. Promising results were registered by the authors during the simulation analysis of the proposed technique. In 2019, Popa et al. [9] incorporated IoT technology for designing an intelligent packaging system for food preservation and safety. The presented framework was capable of identification of bacterial growth, color, pathogens, and volume. Degradation of food-quality was assessed over a time scale. On the contrary, the presented architecture failed to identify environmental factors that have a direct impact on food quality. In 2019, Vellappally et al. [10] presented a medical IoT-tooth sensor to detect the real-time food quality parameters namely, fat content, sugar, and salt. The presented model was designed to acquire data regarding bacterial growth in the mouth based on food quality. The proposed system was deployed in the MATLAB framework for monitoring 15 patients in which 99.23% accuracy was registered. In 2019, Wang et al. [15] applied game theory model for analyzing the traceability system used by the herbal food industry for elucidating strategic choices made by farmers and government officials. Moreover, the authors developed a superior performance by establishing the game equilibrium between the choices. The proposed system was dedicated to incorporate in the herbal product industry for superior performances. In 2020, Sun and Xing [16] incorporated the Evolutionary game methodology to investigate the food supplier and a supermarket relation in China. The authors accumulated the data using the SPSS software over the agriculture supply chain in the form of 5 food parameters including cost, return, size, hitchhiking, and overflows income. These parameters were used in the proposed game model to determine the earning status of the game players. A comparison with the presented framework has been depicted in Table I.

III. PROPOSED MODEL

Figure 2 depicts an overview of the presented technique of smart restaurants for assessing food quality. The proposed approach comprises 4 layers namely Data Acquisition Layer (DAL), Data Categorization Layer (DCL), Data Extraction Layer (DEL), and Gametic-Decision Making Layer (GDML). The detailed functionality of each layer is provided ahead.

A. *Data Acquisition Layer (DAL)*

DAL is the initial layer of the proposed approach for acquiring real-time data values inside the restaurant environment. The major tasks performed in this layer are perceiving and sensing data values about the ambient environment, cleanliness, food products, and utensils in the restaurants. For this purpose, numerous IoT sensors comprising of RFIDs, preceptors, and actuators are displaced in the restaurant environment. In the current study, IoT-data is communicated to a locally connected smart router, and Raspberry Pi acting as fog computing nodes for the local computation. Moreover, fog computing nodes are further connected to the cloud computing

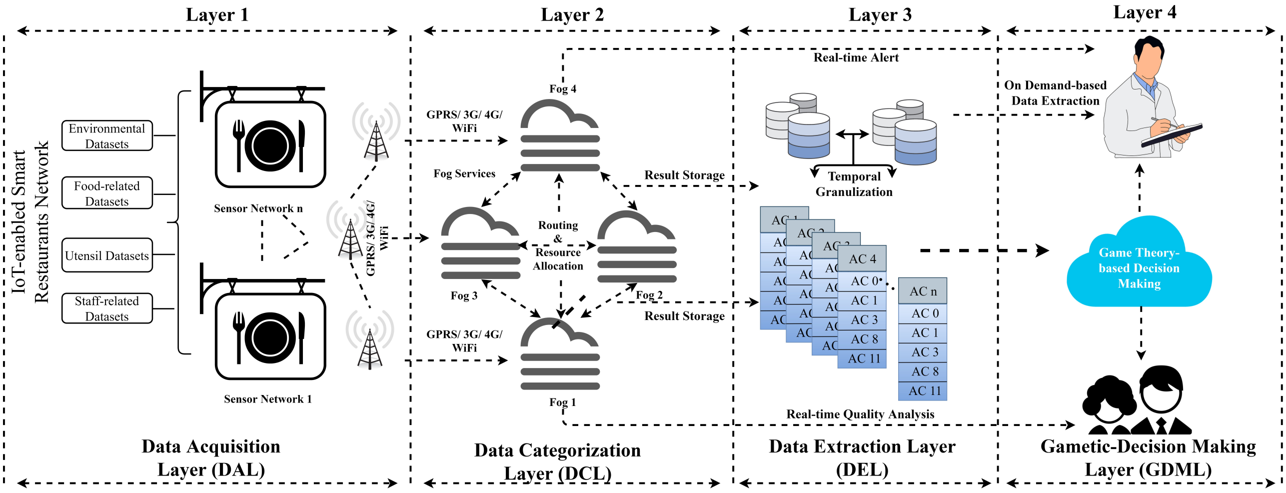

Fig. 2. Layered Framework of the Proposed Model

TABLE II. DATA CLASSIFICATION AND IOT TECHNOLOGY

Classification	Sub-Classification	IoT Technology
Environmental Data	Temperature Humidity Oxygen Level Dust	Temperature Indicator Humidity Indicator SpO2 Device Dust-level Detector
Food-specific Data	Manufacturing Date Preservation Time Date of Expiration Fungus Bacterial Growth	RFID Tags Clock RFID Tags Camera Sensor Camera Sensor
Utensil Data	Corrosion Cleanliness Storage	Rust-level Detector Dust-level Detector Dust-level Detector
Staff-related Data	Behaviour Cleanliness Regularity	Audio Sensor Dust-level Detector Clock Device

platform for the detailed analysis by the healthcare organizations and government officials. Data communication between IoT, Fog, and Cloud is realized using Message Queuing Telemetry Transport (MQTT) Protocol over Wi-Fi. Additionally, security is another important aspect of DAL. Data over the network is secured using Secure Socket Layer (SSL) because of its enhanced efficiency in data protection. Device-based data security is provisioned using Credential Mapping, and User Authentication.

B. Data Categorization Layer (DCL)

IoT-data is comprised of heterogeneous parameters that can have a direct impact on food quality. Conspicuously, it is significant to compile the acquired data values into specific datasets for further analysis. However, before data categorization, it is indispensable to perform data feature abstraction from the heterogeneous data values. Several feature extraction mechanisms including Symbolic Aggregate approximation (SAX), and Cross Modality Search are used for assessing the specific features[17]. DCL performs effective classification of data values into 4 categories including Environmental Data Class (EDC), Food Data Class (FDC), Utensil Data Class (UDC), and Staff Data Class (SDC) as shown in Table II. *EDC* comprises data values focused on the surrounding environment for dust, air, temperature, and humidity. IoT-devices embedded in the nearby pillars, walls, shelves, and tables are dedicated to acquiring such data in a time-sensitive manner. Such data can benefit quality assessment at the storage level and delivery level. *FDC* comprises of food-oriented data values in the form of manufacturing date, expiration date, and temperature value. Sensors including RFIDs, bar code readers, and scanners are capable of perceiving such data efficiently. *UDC* data values are dedicated to acquiring data values from the utensils, and tools utilized in preparation, preservation, and food delivery. Additionally, the data values can also include utensil-specific data like temperature and heat bearing capacity. *SDC* is another data class that can impact food quality severely. Parameters including staff management, cleanliness, preservation, and handling of food are confined to SDC. Henceforth, it is important to acquire such data for enhanced efficacy. However, mere categorization of data features is not sufficient to identify the quality perspective of the food. In the current study, the food quality parameters are further assessed on the basis of a probabilistic parameter of Food Quality Estimate (FQE).

Definition 1: *With the given data segment value v_i acquired at the time instance of t_i, FQE is defined as the adverse impact of v_i and is measured in terms of probability i.e. $P(v_i,t_i)\in(0,1)$.*

FQE presents the quantification estimate to analyze the effect of certain parameters over quality of food. As a result of the estimated FQE measure, the parameter-specific range is prefixed by the quality assurance expert for assessment of the food quality. Additionally, FQE enables classification of the parameters in 2 different classes termed as High-Quality Class (HQC) data and Low-Quality Class (LQC) data. The categorization of datasets is performed using an effective technique of Bayesian Belief Network (BBN). *HQC* data comprises of parameters that do not impact food quality. In other words, parameter values having non-vulnerable impacts are confined to HQC datasets. *LQC* is dedicated to accumulate parameters values that are vulnerable to food quality. Vulnerable parameters like expired food products, high-temperature, and rusty utensils are some examples of LQC data instances. These parameters have both direct and indirect impact on food quality. BBN is the probabilistic classification technique for categorization of datasets into different classes. As an illustration, suppose a data instance is represented as $P_j = (p_1, p_2, ..., p_n)$ where P_j represent the j^{th} food assessment parameter such that all parameters are mutually independent. The conditional probability of food-oriented parameter P_j with respect to class Z_i

is defined by P($\frac{Z_i}{p_1,p_2,...,p_n)}$. However, large number of food quality parameters lead to local confinement and inefficiency. Therefore, the modified BBN is formulated as P($\frac{Z_i}{P_j}$)=$\frac{P(Z_i)P(P_j/Z_i)}{P(P_j)}$. Similarly, probability $P(Z_i)P(P_j/Z_i)$ is refined based on cumulative probability function given by; $P(Z_i)P(P_j/Z_i)$= $P(p_1,p_2,...,p_n, Z_j)$
$=> P(p_1/p_2,...,p_n, Z_i)P(p_2,...,p_n, Z_i)$
$=> P(p_1/p_2,...,p_n, Z_i)P(p_2/p_3,...,f_n, Z_i)P(p_3,...,p_n, Z_i)$
$=> P(p_1/p_2,...,p_n, Z_i)P(p_2/p_3,...,p_nZ_i),..., P(p_{n-1}/p_n,...,p_nZ_i)$
$*P(p_n/Z_i)P(Z_i)$
Moreover, it is assumed that each feature p_j is individualistic and not dependent on other feature p_i such that $j \neq i$. Then $P(p_j/p_{j+1},...,p_n, Z_i)= P(p_j/Z_i)$. Therefore, the joint probability is formulated as $P(Z_i)=\Pi_{j=1}^{n}$ $P(Z_i)P(p_j/Z_i)$ $=> P(\frac{Z_i}{p})= \Pi_{j=1}^{n}$ $P(Z_i)P(Z_j/Z_i)/P(p)$ where Z_i denotes the HQC and LQC class of parameters.

C. Data Extraction Layer (DEL)

DEL is confined to mine the data segments acquired ubiquitously by the IoT devices. The extraction of useful data segments from the repository is important for the overall food quality assessment as it provides the deep data inspection technique for data analysis. Based on data acquired in the HQC and LQC datasets, each of the data segments is associated with the temporal feature for time-sensitive analysis at the fog computing platform. In the current research, this task is performed by the Temporal Extraction technique for analysis of time-based data values [18]. However, mere temporal data extraction does not provide specific time-based data segments. Henceforth, this study proposes a novel Temporal Granulation mechanism for sliding window-based data assessment. Temporal granulation provides effective data abstraction and accumulation for certain parameters based on the specific time-scale. In other words, data segments are extracted based on the given slot of Δt. It is formalized as $<v_1,t_1>$, $<v_2,v_2>$,...,$<v_n,t_n>$, where v_j indicates value of j^{th} feature at a given instance t_j such that $t_j \rightarrow \Delta t$. The unanimity obtained from granulation will enable effective analysis of food quality parameters over common scale. Additionally, such slot-based feature assessment will enable feasible quantification of food quality in terms of Quality Support Index (QSI). QSI is the quantifiable estimate of the food-quality over temporal scale $<v_1,t_1>$, $<v_2,t_2>$,...,$<v_n,t_n>$in a time slot of Δt. QSI associates a quantifiable estimate with the heterogeneous food-oriented parameters detected with IoT devices using the FQE value. In other words, more value of QSI indicates better food quality and vice-versa. The specific steps for the determination of QSI are mentioned in Table III. Initially, numerous parametric values are contrasted with the threshold estimate. If the acquired value is more than the pre-defined measure value then *weight∗FQE* is summed to the QSI, otherwise, 0 is summed. After aggregation of numerous values, it is averaged of the number of parameters for scaling purpose such that QSI $\in(0,1)$, such that 0 indicate low quality of food and 1 indicate better quality of food. For minimization of temporal delay, the proposed model incorporates the Max-Min algorithm procedure of resource scheduling[19]. Temporal Delay (TD) depicts the aggregation of Processing Time (PT) and Routing Delay (RD) for data transmission at time Δt. Mathematically, PT for data segment t_x at fog $node_y$ is expressed as $PT_{xy}(\Delta t) = S_x(\Delta t)\ \phi_x/R_y(\Delta t)$, where $S_x(\Delta t)$ denotes the data size of x^{th} segment, ϕ_x denote the computing intensity, and $R_y(\Delta t)$ denotes available computing resource of y^{th}fog node. Similarly, the RD for x^{th} data segment is time taken in transmitting the data segment to the cloud respiratory via fog node and is computed as $RD_{xy}(\Delta t)=S_x(\Delta t)/r_{xy}(\Delta t)$ + K, where $r_{xy}(\Delta t)$ is the communication rate between end-device and fog node i.e. $r_{xy}(\Delta t)=\gamma * log_2(1+ (c(\Delta t)*p(\Delta t))/\delta)$, where γ indicates the network bandwidth, δ is the noise power, $c(\Delta t)$ indicates the channel power gain, $p(\Delta t)$ is the transmission power, K denotes the fog-cloud routing delay. Henceforth, $TD_x(\Delta t) = PT_{xy}(\Delta t) + RD_{xy}(\Delta t)$.

TABLE III. QSI ESTIMATION PROCEDURE

Algorithm 1: QSI Estimation
Input: IoT data and associated FQE values. α_1, α_2, α_3, α_4 are the weights of food quality parameters. **Step 1**: Initialize $FQE_{\Delta t} = 0$. **Step 2**: Equate FQE measure of 1^{st} parameter with threshold. **Step 3**: If $FQE_1 > \lambda_1$, Then Add α_1*FQE_1 to QSI. **Step 4**: Equate FQE measure of 2^{nd} parameter with threshold. **Step 5**: If $FQE_2 > \lambda_2$, Then Add α_2*FQE_2 to QSI. **Repeat for n parameters** **Step 6**: Equate FQE measure of n^{th} parameter with threshold. **Step 7**: If $FQE_n > \lambda_n$, Then Add α_n*FQE_n to QSI. **Step 8** : $QSI = 1- \frac{1}{n}(\alpha_1*FQE_1+\alpha_2*FQE_2+\alpha_3*FQE_3+ ...+\alpha_n*FQE_n)$

D. Gametic-Decision Making Layer (GDML)

GDML is the final layer of the presented technique of food quality assessment. In the current study, 2-player gametic-decision modeling has been presented for food quality assessment. Specifically, a decision-model is designed between Player-1 i.e. users, and customers and Player-2 i.e. restaurant chefs, and food quality managers. Both players are characterized by a certain set of strategies for the overall analysis of food quality and decision-making. Specifically, Player-1 is characterized by 2 types of strategies including C_{Prefer} and $C_{Non-Prefer}$. These strategies will determine the customers behavior for visiting the restaurant or not, based on the food-quality. Similarly, Player-2 is confined to 2 strategies namely $C_{high-quality}$ and $C_{low-quality}$ where $C_{high-quality}$ indicates better food quality and $C_{low-quality}$ depicts low food quality provided to the customers.

1) Game Constraints: Game constraints define the estimate to select certain strategy by the game-player. Moreover, it describes the measure to maximize the profit or benefit to the player by adopting a strategy. 5 probabilistic game constraints have been defined in the current research. Specifically, P(r) denotes the restaurant ranking in terms of food quality assessment. P(s) denotes the probability of income/turnover generation for the restaurant owners, which can be increased or decreased based on the number of customers. Similarly, P(p), P(f), P(q) denotes personalized healthcare, feedback, and service quality respectively, for the decision-making.

2) Game Utility: Strategy Set and Game constraints mentioned previously formulates the basis of the presented 2-player game-based decision-making. The overall objective of the game model to acquire utility measure based player's respective strategy. Let $P_{Player-1}$ and $P_{Player-2}$ be the utility for both players of the game model. Henceforth, based on the strategy set, the following 4 scenarios have been formalized.

Scenario 1: Player-1$\rightarrow$ C_{Prefer}, Player-2$\rightarrow$ $C_{High-Quality}$: In this scenario, the utility measure is estimated depending on the strategy adopted by both players. For Player-1, P(p) will rise as high quality of food is consumed. Moreover, Player-1 will provide better feedback for the restaurant and increases P(f) measure.

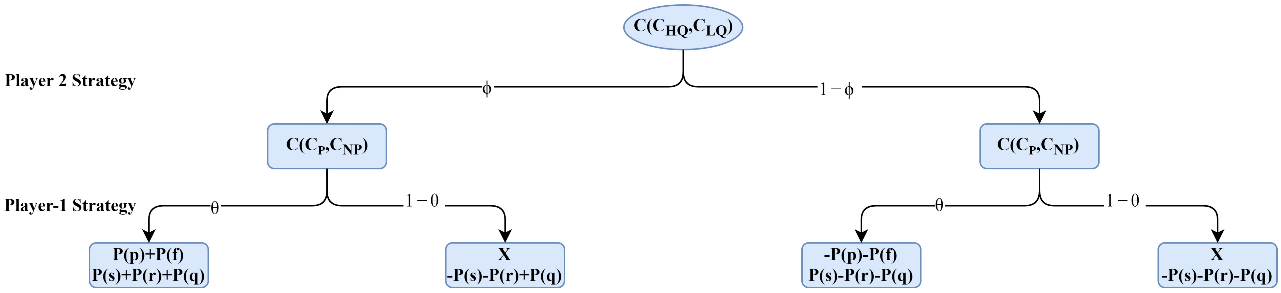

Fig. 3. Game Tree; C_{HQ}: High-Quality Strategy and C_{LQ}: Low-Quality Strategy; C_P: Prefer Strategy and C_{NP}: Non-Prefer Strategy

Henceforth, the total utility for Player-1 is P(p)+P(f). Likewise, provisioning better food quality will increase the number of customers i.e. P(s), ranking (P(r)) and quality of service P(q). The total utility function for the Player-2 will be P(s)+P(r)+P(q).

Scenario 2: Player-1$\rightarrow$ C_{Prefer}, Player-2$\rightarrow$ $C_{\text{Low-Quality}}$: This scenario depicts the scenario when the quality of preserved food is poor and the customer still tends to visit the restaurant. In this case, the probability of healthcare and feedback will be negative i.e. -P(p) and -P(f). Therefore, Player-1 utility will be -P(p)-P(f). For Player-2, the customer visits the restaurant to increase the turnover i.e. +P(s). However, due to negative feedback, the ranking probability P(r) and service quality P(q) will decrease. The overall utility is computed as P(s)-P(r)-P(q).

Scenario 3: Player-1$\rightarrow$ $C_{\text{Non-prefer}}$, Player-2$\rightarrow$ $C_{\text{High-Quality}}$: In this scenario, the customer is not preferring the restaurant even if the quality of food is better. There can be several factors including increased financial cost, and more traveling distance. Henceforth, P(h) and P(f) will be don't care condition i.e. X. For Player-2, the overall turnover will be decreased due to fewer customers i.e. -P(s). Moreover, the parameters P(r) will decreased due to no feedback and P(q) will be increased due to better food quality. This led to the overall utility numerating to -P(s)-P(r)+P(q).

Scenario 4: Player-1$\rightarrow$ $C_{\text{Non-prefer}}$, Player-2$\rightarrow$ $C_{\text{Low-Quality}}$: In this case scenario, the customer acquires non-visiting behaviour towards the restaurant as the result of non-acceptable quality of food. This is due to personal judgment, and experience. However, provisioning poor food quality will decrease the overall turnover, ranking and service quality. Based on these, the overall payoff for Player-1 is computed as X and for Player-2 it is -P(s)-P(r)-P(q).

3) Game Tree: Figure 3 shows the formulation of the game tree based on 4 decision scenarios mentioned previously. Additionally, the strategy set for both players is adopted over a probability basis. Therefore, let (θ) be the Player-1's probability to select C_{Prefer} strategy, then (1-θ) is the probability $C_{\text{Non-prefer}}$ strategy. Similarly, Player-2 adopts $C_{\text{High-Quality}}$ strategy based on probability (ϕ) and $C_{\text{Low-Quality}}$ strategy based on probability (1-ϕ).

4) Game Equilibrium: The game-theoretic decision-making modeling technique is optimized by the balanced strategy between players considered as Nash Equilibrium[20]. Conspicuously, the equilibrium strategy is determined for the overall decision-making.

Payoff: Player 1 : *In this scenario, the equilibrium result is determined when Player-1 follows strategy of C_{Prefer} and Player-2 selects $C_{High\text{-}Quality}$ strategy and when Player-1 selects $C_{Non\text{-}prefer}$ strategy and Player-2 selects $C_{Low\text{-}Quality}$ strategy.*

Based on the game tree, the equilibrium is established as;

=>θ(P(p)+P(f))+ϕ(P(s)+P(r)+P(q))=
(1-θ)P(X)+(1-ϕ)(-P(s)-P(r)-P(q))
=>θP(p)+θP(f)+ϕP(s)+ϕP(r)+ϕP(q)=
P(X)-θP(X)-P(s)-P(r)-P(q)+ϕP(s)+ϕP(r)+ϕP(q)
$=>\theta = \frac{P(X)-P(s)-P(r)-P(q)}{P(p)+P(f)+P(X)}$

Payoff: Player 2 : *In this scenario, the equilibrium is determined when Player-1 selects strategy of $C_{Non\text{-}prefer}$ and Player-2 selects $C_{High\text{-}Quality}$ strategy and when Player-1 selects C_{Prefer} strategy and Player-2 selects $C_{Low\text{-}Quality}$ strategy.*

According to the game tree,

=>θ(-P(p)-P(f))+ϕ(P(s)-P(r)-P(q))=
(1-θ)P(X)+(1-ϕ)(-P(s)-P(r)+P(q))
=>-θ(P(p))-θ(P(f))+ϕP(s)-ϕP(r)-ϕP(q)=
P(X)-θP(X)-P(s)-P(r)+P(q)-ϕP(s)-ϕP(r)+ϕP(q)
=>2ϕ(P(r))= θ(-P(p)-P(f)+P(X))-P(X)+P(S)+P(r)-P(q)

Putting θ from Player-1 Utility and considering don't care P(X) accordingly we get

2ϕ(P(r))=2(-P(X)+P(S)+P(r)-P(q))
$=>\phi = \frac{-P(X)+P(S)+P(r)-P(q)}{P(r)}$

Both Player's Payoff estimates the probabilistic measure for selecting strategy in order to maximize the respective profits. In other words, restaurant owner will provide better food quality for increasing total income. Similarly, customer prefer high quality food for healthcare safety. In the game tree, (1-θ) and (1-ϕ) is equated to QSI value determined earlier for real-time analysis of the food quality. Henceforth, the mixed profile are given by (θ, 1-θ) and (ϕ,1-ϕ) for Player-1 and Player-2 respectively. Moreover, the efficiency of game model is determined by the analysis of the replicator equations for evolutionary stable strategy (ESS). Table IV presents the mathematical evaluation for the ESS. It is deduced that the presented decision-modeling persists ESS at the nash equilibrium points and is therefore immensely effective. The convergence of the proposed game model is estimated over temporal instances as shown in Table V. It can be depicted that the presented payoff model attain nash equilibrium (maximal accuracy) over the passage of time. Additionally, the error generation is decreases with the accumulation of large datasets. Henceforth, over the passage of time, the resultant owners improves the quality of food and destructive parameters will eventually fade over time.

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TABLE IV. EXISTENCE OF EVOLUTIONARY STABLE STRATEGY(ESS) AT NASH-EQUILIBRIUM POINTS

<table>
<tr><th>Replicator Equation for Player-1</th><th>Replicator Equation for Player-2</th></tr>
<tr><td>E(1)=θ(P(p)+P(f))+(1-θ)(P(X))
E(2)= θ(-P(p)-P(f))+(1-θ)(P(X))
E(12)=ϕ(E(1))+(1-ϕ)(E(2))
E(12)=2$\theta\phi$(P(p)+P(f))-θ(P(p)+P(f)-2P(X))+ϕP(X))+P(X)
RE(Player-1)=ϕE(12)-(1-ϕ)(E(1))
For ESS, RE(Player-1)=0
Solving, we get ϕ^2(2θP(p)+2θP(f)+P(X)+1)=0
(ϕ,θ)=(0,1)</td><td>E'(1)= θ(P(s)+P(r)+P(q))+(1-θ)(-P(s)-P(r)+P(q))
E'(2)= θ(P(s)-P(r)-P(q))+(1-θ)(-P(s)-P(r)-P(q))
E'(12)=ϕ(E'(1))+(1-ϕ)(E'(2))
E'(12)=2(θP(s)+ϕP(r)+P(q))-P(s)-P(r)-P(q)
RE(Player-2)=ϕE'(12)-(1-ϕ)(E'(1))
For ESS, RE(Player-2)=0
2(ϕ^2(P(r)+P(q))+θ(P(s)+P(r))-ϕP(r))-P(s)-P(r)-P(q) =0
(ϕ,θ)=(0,1)</td></tr>
<tr><td colspan="2">Based on Replicator Equation for Player-1 and Player-2, Non-Nash Equilibrium (ϕ,θ)=(0,0),(0,1),(1,1),(1,0)
Nash Equilibrium points=($\frac{P(X)-P(s)-P(r)-P(q)}{P(p)+P(f)+P(X)}$, $\frac{-P(X)+P(S)+P(r)-P(q)}{P(r)}$)
Determinant and Trace value of Jacobean = $(+ve,+ve)_{(0,0)}$, $(-ve,+ve)_{(0,1)}$,$(-ve,-ve)_{(1,1)}$,$(+ve,+ve)_{(1,0)}$,$(+ve,-ve)_{\text{Nash Points}}$
The positive value of determinant and negative value of trace for the Jacobean at Nash-equilibrium Points depicts ESS.</td></tr>
</table>

TABLE V. TEMPORAL EQUILIBRIUM CONVERGENCE

Game-Theoretic Convergence over Time Scale
Lemma 1: The game theoretic strategy sequence s_n at time t_n converges to σ in n time intervals where σ denotes the Nash Equilibrium i.e (s_n, t_n)$\rightarrow\sigma$ **Proof**: Assume σ to be not a Nash Equilibrium   Then, There exists $s_i \in$S (Strategy Sequence) with $\sigma_i>0$ such that for Payoff P, P(s_i, σ_i)>P(s_n, σ_n).   According to Replicator Dynamics of Table IV, Choose ε(accuracy error) >0 such that, $\varepsilon<\frac{1}{2}$(P(s_i, σ_i)-P(s_n, σ_n)) and $\forall t_i \rightarrow t_n$, P^T(RE($Player_i$)-P(s_i, σ_i)) $<\frac{\varepsilon}{Max(P^t)}$ which is possible as $P^t \rightarrow \sigma_i$. For very large time scale t>T we have P(s_i,t_i)= $\sum_{s_i}$P(s_n,t_n)RE(P(s_{n-1},t_{n-1})) $\leq\sum_{s_i}$P(s_n,t_n)σ_i,t_i+ ε $<\sum_{s_i}$P(s_i,t_i)σ_i,t_i- ε $\leq$ P(s_n, σ_n). This result shows that after sufficiently large t, s_i is never played by the $Player_i$ implying that as t$\rightarrow\infty$, P(s_i,t_t)$\rightarrow$0. But this contradict the fact as $\sigma_i>0$. Hence completing the proof.   Generically, the strategy sequence s^t converges to Nash equilibrium(σ) in the time-average sense iff $\forall$ i and $s^t \in$S(Strategy Set), $\lim_{T\rightarrow\infty}\frac{\sum_{t=0}^{t=T-1}P(s^t=s)}{T}=\sigma_i$

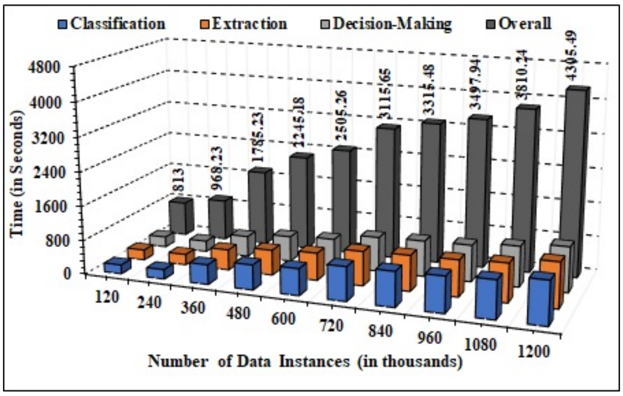


Fig. 4. Cumulative Temporal Delay Analysis

IV. EXPERIMENTAL IMPLEMENTATION

The proposed approach incorporates a 2-player game-theoretic decision-modeling in IoT-inspired smart restaurant environment for effective food quality assessment. The proposed system is validated based on; (a) Temporal Delay efficiency for computation; (b) Data Classification efficiency for food quality assessment; (c) Statistical effectiveness of the presented approach for decision-making efficiency; (d) Determining the reliability of the proposed model. For simulation purposes, 4 challenging datasets were considered, namely REST1[3] comprising of 2,00,413 data values, REST2[4] comprising of 2,71,633 data values, REST3[5] comprising of 2,71,214 data values and REST4[6] comprising of 5,31,250 data values. Each of the datasets was processed over Raspberry Pi v3 as a fog computing device using FogBus and Amazon EC2 cloud computing platform. Data classification was performed using WEKA open-source toolkit. Game model-based decision-making was implemented over GAMBIT open-source toolkit.

A. Temporal Delay Efficiency

Temporal Delay efficiency (T_{Delay}) determines the execution delay effectiveness for the proposed model. Specifically, it is defined as the time taken by the proposed model to classify, extract and decision-making by the proposed model.
Mathematically, $T_{Delay}=T_{Classify}+T_{Extract}+T_{Decision\text{-}Making}$. The implementation results registered for the proposed model are cumulatively depicted in Figure 4. For REST1 datasets, the classification delay averages to 115.36s. This is followed by the average temporal delay of 119.36s and 122.36s for data extraction and gametic-decision making. REST2 dataset was tested for estimating the temporal performance. In this scenario, the presented approach registered the delay of 118.36s for classification, 123.26s for data mining and 125.56s for decision-making. In the simulation with the REST3 dataset, the average temporal delay for classification, data extraction, and decision-making was numerated to 119.02s, 123.99s, 125.59s respectively. Finally, the REST4 dataset was assessed for estimation of system performance. In this case, overall delay enumerated to 431.18s which consists of 136.26s for classification, 142.23s for data mining and 152.69s for decision-making. This depicts that minimal temporal delay has been registered for the overall computation.

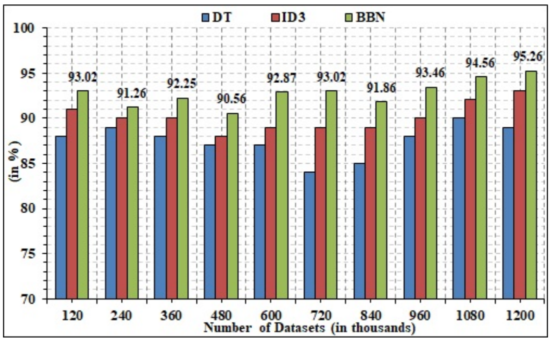
B. Classification Efficiency

Classification efficiency has been evaluated in terms of Sensitivity, Specificity, and Accuracy as shown in Figure 5. As the baseline classifier, 2 state-of-the-art data classifiers have been incorporated, namely Decision Tree (DT) and ID3 technique. However, the remaining model was unaltered during simulation. For specificity estimation, the proposed model acquired an average value of 92.91%. Comparatively, DT and ID3 were able to register values of 89.03% and 90.26% respectively as shown in Figure 5(a). The accuracy measure for the presented approach averaged to 93.88% as compared to 90.26% for DT and 91.89% for ID3 (Figure 5(b)). Enhanced values of sensitivity (93.30%) was registered for the proposed model as compare to DT and ID3 (Figure 5(c)). Henceforth, in the current scenario, proposed approach is superior as compared to other techniques.

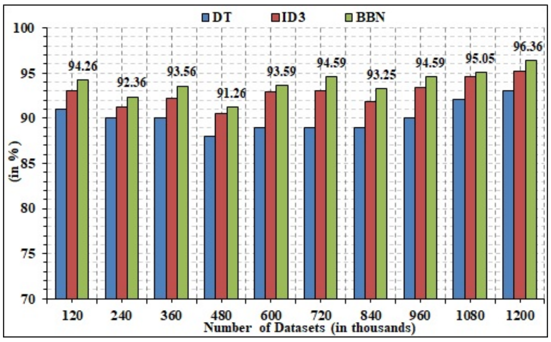
C. Statistical Efficiency

Statistical Efficiency is concerned with the decision-making effective for the proposed game-theoretic model for food quality assessment. For estimating the performance enhancement, the comparative analysis has been performed based on state-of-the-art baseline models

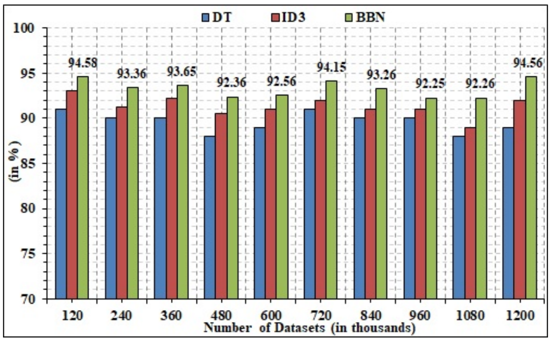
[3]Source:https://data.world/davidtalby/
[4]Source: https://data.world/kingcounty/f29f-zza5/
[5]Source:https://data.world/kingcounty/w8jk-da8e/
[6]Source:https://data.world/healthdatany/aaxz-j6pj/



(a) Specificity



(b) Accuracy



(c) Senstivity

Fig. 5. Cumulative Classification Efficiency

of Convolutional Neural Network (CNN)[21], Enhanced Support Vector Machine (ESVM)[22], and Decision Tree (DT)[23]. The performance is determined in terms of Sensitivity, Accuracy, Specificity, and F-measure. Moreover, the system is also analyzed for error estimation in terms of Relative Absolute Error (RAE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Root Relative Squared Error (RRSE). Table VI shows the acquired cumulative results for the presented technique. It is seen that the proposed mechanism registers better performance for sensitivity (94.56%), accuracy (94.37%), specificity (93.24%), and f-measure (94.29%) in comparison to CNN, ESVM, and DT. Additionally, the error generated in overall food quality analysis is comparatively low as compared to other models. Specifically, the presented model acquired a minimal RMSE and MAE value numerating to 3.15±0.07% and 3.03±0.14% respectively. Furthermore, low values of RAE (3.23±0.22%) and RRSE (3.19±0.22%) depicts the overall effectiveness of the proposed model. Henceforth, the presented technique is more efficient and effective in decision-making as compare to other decision-making techniques.

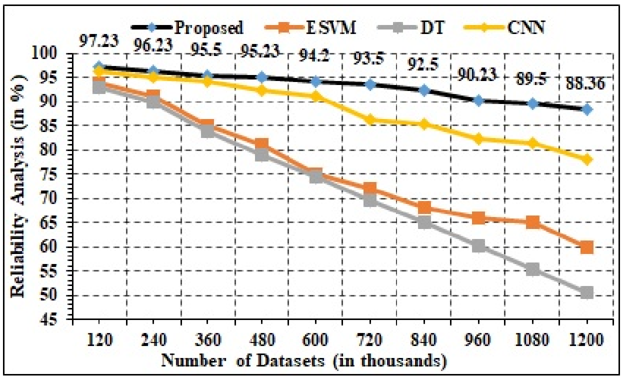


Fig. 6. Cumulative Reliability Analysis

D. Reliability Analysis

It is concerned with the dependability assessment of the proposed approach. It estimates the overall system performance for error tolerance. Figure 6 shows the graphical overview of the comparative results acquired for the presented approach. Cumulatively, 93.39% of reliability was registered for the presented approach over the number of datasets. Comparatively, CNN registered an average reliability value of 90.02%, ESVM acquired 85.36% value and K-NN attained 82.01% value. Henceforth in the current scenario, it is concluded that the presented game-theoretic approach is more reliable in comparison to other decision-modeling techniques.

V. Conclusion

IoT-Fog-Cloud has provided significant enhancements in several domains of its applicability. Inspired by this, the current research presents a novel vision of the IoT-inspired Smart Restaurant for assessing the quality of food in real-time. The proposed approach is divided into 4 layers including Data Acquisition Layer (DAL), Data Categorization Layer (DCL), Data Extraction Layer (DEL), and Gametic-Decision Making Layer (GDML) for realizing the overall objective. Specifically, the food quality is quantified over a temporal basis in terms of probabilistic parameters of the Food Quality Estimate (FQE) and Quality Support Index (QSI). The decision-making is performed using the 2-player game theory for quality assessment of food over real-time parameters. The proposed model is simulated using 4 challenging datasets and results are compared with several state-of-the-art decision-making models for performance enhancement. Based on the results, it is concluded that the presented approach is immensely effective and efficient in assessing the quality of food in a smart environment. For future research purposes, the presented approach can be enhanced to incorporate seasonal food quality over small food hubs, and sellers. Additionally, research can be carried out to connect multiple-restaurants for food standard adoption.

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TABLE VI. STATISTICAL EFFICIENCY

Parameter	CNN	ESVM	DT	Proposed
Sensitivity	90.02%	89.16%	84.17%	94.56%
Accuracy	91.23%	90.32%	86.33%	94.37%
Specificity	89.29%	88.34%	86.95%	93.24%
F-Measure	90.96%	88.30%	87.15%	94.29%
Root Mean Square Error (RMSE)	4.42±0.05%	5.21±0.06%	5.50±0.48%	3.15±0.07%
Mean Absolute Error (MAE)	4.59±0.06%	5.66±0.35%	6.98±0.33%	3.03±0.14%
Relative Absolute Error (RAE)	4.75±0.19%	5.98±0.16%	6.99±0.19%	3.23±0.22%
Root Relative Squared Error (RRSE)	4.97±0.18%	5.21±0.08%	5.98±0.92%	3.19±0.22%

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