A Fuzzy-Neural Network Approach to Market Supervision and Product Recall Prediction

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***Abstract*—The paper suggests a fuzzy-neural network market monitoring and product recall prediction method. This method uses fuzzy logic and neural networks to handle complex and ambiguous input. The fuzzy logic component fuzzes product quality, customer complaint, and market trend index input variables. The neural network component learns fuzzified data patterns to predict product recalls. Online information is used for product recalls. Customer complaint rate, product quality rating, and market trend index are in this dataset. Fuzzy sets and membership functions finish input variable fuzzying. A neural network trained on fuzzified data predicts product recalls. We assess the proposed method's accuracy, precision, recall, and F1-score. After testing, the suggested technique had an accuracy of 0.863, precision of 0.854, recall of 0.872, F1-score of 0.863, and MSE of 0.123. The fuzzy-neural network technology improves market monitoring and product recall predictions. Fuzzy logic and neural networks analyze complicated and unexpected data, improving prediction accuracy. This strategy may assist market supervisors and manufacturers decide on product recalls.**

Keywords*—Fuzzy-neural network; customer complaint rate; product quality rating; market trend index; market supervision; accuracy; precision; recall; F1-Score and MSE

I. Introduction

Deep learning has become a very viable field of research because to recent technological breakthroughs that have enhanced computational power at relatively affordable costs. The advancement of deep learning techniques has enabled the execution of many complex modeling tasks with precision and reliability. Methods for predicting time series analysis based on deep learning have been documented [1-3]. Concerns about human interpretability arise when deep learning networks derive insights from data [4, 5]. These challenges arise when deep learning models become increasingly complex with additional layers. Models are depicted as opaque entities with concealed representations and computations within the network, rendering them challenging to comprehend [6]. Interpretability is essential in several fields. Nonetheless, concepts of machine learning interpretability remain contentious. This is due to the fact that various domains and contexts possess distinct meanings [7]. Interpretability refers to the capacity to comprehend and elucidate the decision-making processes of a model [8]. It may also encompass qualitative understanding of the correlation between input and output attributes [9, 10]. Recent years have seen an increase in research on explainable Artificial Intelligence (XAI) aimed at improving the interpretability of deep learning [11, 12].

Fuzzy and Bayesian logic are employed in certain systems to derive conclusions and facilitate decision-making. Various systems employ both types of reasoning. Domain specialists typically formulate fuzzy logic rules and provide comprehensible knowledge insights [13]. Observing the activation of rules inside the fuzzy system enhances interpretability [14]. Fuzzy logic can manage erroneous, ambiguous, or poorly specified data similarly to human experts [15]. Nonetheless, the human curation of fuzzy rules for a complicated model is arduous and time-intensive. Recent advancements have presented fuzzy neural networks (FNN) or neuro-fuzzy computing (NFC) as a substitute for fuzzy systems [16]. It is feasible to integrate neural network learning with fuzzy logic for enhanced semantic transparency and interpretability [17]. Fuzzy logic can analyze inputs and outputs of deep learning models derived from noisy, varied, incomplete, or erroneous data. The training of deep learning models utilizing fuzzy logic systems is expedited [18]. Fuzzy neural networks are utilized in several domains to address real-world issues due to their advantages.

A stock price prediction model based on a time-series recurrent neural network has been documented [19, 20]. Recent attention has been on the application of machine learning in predictive systems characterized by frequent alterations in data, patterns, and trends, exemplified by financial market forecasting [21-27]. The comparison of state-of-the-art approaches is shown in Table I.

Market surveillance and product recall forecasting are essential for consumer safety and market confidence. Nonetheless, the complexity and volatility of market data may impede accurate forecasting and prompt market intervention. This is due to the dynamic and complicated nature of market data. Conventional market surveillance and product recall forecasting methods depend on human analysis of historical data. This approach may be sluggish, imprecise, and ineffectual in identifying safety hazards. Artificial intelligence and machine learning have created new opportunities for enhanced market surveillance and product recall forecasting systems. This study culminates with an innovative fuzzy-neural network methodology. This system utilizes fuzzy logic and neural networks to manage intricate market data. Table II delineates the principal contributions, limits, and prospective avenues for the planned study. This study enhances market oversight and forecasts for product recalls in several dimensions. This research culminates in an innovative fuzzy-neural network methodology. This system utilizes fuzzy logic and neural networks to manage intricate market data. Current approaches predict product recalls with worse accuracy and efficacy compared to the suggested methodology. Imprecision in market data is addressed by the utilization of fuzzy-neural networks.

This method provides a more precise estimation. It affects market surveillance and product recall forecasting. It assists authorities and enterprises in making educated, data-driven decisions.

The rest of the paper is structured as follows: Section II presents details about the proposed model; Section III presents experimental set and working examples; Section IV presents results and discussion and Section V draws conclusion.

TABLE I COMPARISON AMONG STATE-OF-THE-ART METHODS

Reference	Methodology	Key Findings/Contribution	Relevance to Fuzzy-Neural Network Approach
[21]	An explainable evolving fuzzy neural network	The study focuses on using neural networks to predict product recalls by analyzing historical data.	Neural network methods could be integrated with fuzzification in predicting recalls.
[22]	Decision support systems	The study discusses how fuzzy systems support decision-making in volatile market conditions.	Fuzzy decision-making mechanisms are key for the fuzzy-neural network model.
[23]	Deep Neuro-Fuzzy System	DL techniques are applied to predict product recalls based on various risk factors and market conditions.	Could provide additional data features for training neural networks in recall prediction.
[24]	Multilayer fuzzy neural networks	Combines fuzzy logic and neural networks to predict food safety risks and recalls in the food industry.	Directly relevant, as it combines fuzzy and neural network models for recall prediction.
[25]	Machine learning based market surveillance	Neural networks are applied to monitor and predict market safety and product risks.	Neural networks are essential for monitoring and predicting recall outcomes in the approach.
[26]	Fuzzy neural network algorithm	Uses fuzzy logic to predict market demand, which is integrated with recall decision-making.	Fuzzy logic can be applied for market demand prediction in recall decision support.
[27]	Deep learning and fuzzy systems	A review that covers various applications of neural networks in product recall prediction across industries.	This provides a foundational understanding of how neural networks are applied to product recall predictions.

TABLE II KEY CONTRIBUTION, LIMITATIONS AND FUTURE DIRECTIONS OF THE PROPOSED WORK

Application	Key Findings/Contributions	Limitations	Future Directions
Fuzzy Logic in Decision Making	- Handles uncertainty and imprecision effectively. - Provides a framework for representing human expertise and knowledge.	- Difficulty in determining optimal membership functions - Potential for rule explosion in complex systems.	- Development of more robust methods for membership function optimization. - Integration with other AI techniques (e.g., deep learning).
Neural Networks for Prediction	- Excellent pattern recognition and learning capabilities. - Can handle complex non-linear relationships.	- Black-box nature can make interpretation difficult. - Prone to overfitting.	- Development of more interpretable neural network architectures - Techniques for improving generalization and robustness.
Fuzzy-Neural Networks	- Combines the strengths of fuzzy logic and neural networks. - Improved interpretability compared to traditional neural networks. - Can handle uncertainty and imprecision effectively.	- Complexity in designing and training hybrid architectures. - Limited interpretability compared to purely rule-based fuzzy systems.	- Investigation of novel hybrid architectures and optimization algorithms.
Market Supervision and Product Recall	- Traditional methods often rely on reactive measures. - Proactive prediction can significantly reduce costs and improve consumer safety.	- Limited availability of high-quality data. - Difficulty in capturing complex interactions between factors.	- Development of robust data collection and preprocessing techniques. - Incorporation of real-time data streams and social media analysis.

II. MODULE IMPROVEMENTS

A. Integration of Fuzzy Logic and Neural Networks

The fuzzy logic component encompasses fuzzification, which transforms precise input data into fuzzy sets by membership functions such as triangular, trapezoidal, or Gaussian. Fuzzy rules are established by expert knowledge or data analysis to encapsulate the connections among input variables. Fuzzy inference system utilized for fuzzy input data to generate fuzzy output. Inputs from the fuzzy logic component are sent into the input layer of the neural network component. The concealed layers process ambiguous inputs using neural network architecture. The output layer produces accurate estimations of product recall probabilities. Fuzzy logic integrated with neural networks constitutes the Fuzzy-Neural Network Architecture. Fuzzy-Neural Network Training utilizes market data and expert knowledge to train fuzzy-neural networks. The trained fuzzy-neural network forecasts the likelihood of product recall utilizing current market data. Neural networks discern intricate patterns, whereas fuzzy logic addresses data ambiguity. Fuzzy logic and neural networks enhance forecast precision and resilience. Neural networks elucidate intricate linkages, whereas fuzzy logic produces interpretable outcomes.

Fig. 1 illustrates that the nodes designated as "Product Quality Rating (PQR)", "Customer Complaint Rate (CCR)", and "Market Trend Index (MTI)" are the main inputs for market data, product attributes, and market conditions. This is apparent from the fact that these nodes constitute the most significant inputs. Fuzzy membership functions are employed to convert inputs into fuzzy sets. These fuzzy sets are represented by the terms "Fuzzy Market Data", "Fuzzy Product Risk", and "Fuzzy Market Condition". The generation of predictions necessitates the processing of fuzzy sets using fuzzy rules, such as IF-THEN conditions, which are integrated with a neural network. "Recall Prediction (Fuzzy Output)" refers to the output that represents the fuzzy forecast of product recalls.

The processing of data yields fuzzy market data, fuzzy product risk, and fuzzy market conditions through the use of fuzzy membership functions. This approach has yielded the results depicted in Fig. 2. These are many iterations of the inputs that have been amalgamated in a disordered fashion. Nodes 1, 2, and 3 constitute a neural network that analyzes ambiguous inputs. This indicates that there are weights (w1, w2, etc.) linking each hidden node to every fuzzified input, such as Fuzzy Market Data. An example of this type of data is Fuzzified Market Data. These weights delineate the extent of correlation between each input and all other inputs. A Recall Prediction indicates the probability of a product recall. The inputs used into the analytical process are the foundation of this projection. The backpropagation loop illustrates this process by showing how the network enhances its predictive capabilities by modifying its weights in reaction to prediction errors. A crucial element of the learning process is the modification of weights for each input, determined by the mistake generated by the preceding input. Fig. 2 exemplifies the integration of the fuzzy logic component, encompassing the fuzzification of inputs, with neural network processing, which comprises hidden layers, output, and learning through backpropagation, into a unified model aimed at predicting product recalls.

B. Model's Predictions with Example Fuzzy Rules and their Impact on Decision-Making

A significant amount of information might be gained by regulators and manufacturers if they examine the forecasts of the model via the lens of fuzzy rules as an example. These fuzzy rules, which are derived from expert knowledge and insights driven by data, provide a transparent and open framework for understanding the interactions that occur between the various factors that influence the probability of product recall using fuzzy logic. A fuzzy rule such as "IF defect rate is HIGH, THEN recall likelihood is HIGH" for example clearly shows how defect rate affects model predictions. Manufacturers and authorities may better grasp the decision-making process and affect product safety and recall processes by means of analysis of these fuzzy rules and projections. Finally, this transparent and easily available approach enables stakeholders to make fact-based decisions and trust the forecasts of the model, hence lowering risk and maximizing outcomes. Fig. 3 presents that regulators and manufacturers can interpret the model's predictions with example fuzzy rules and their impact on decision-making.

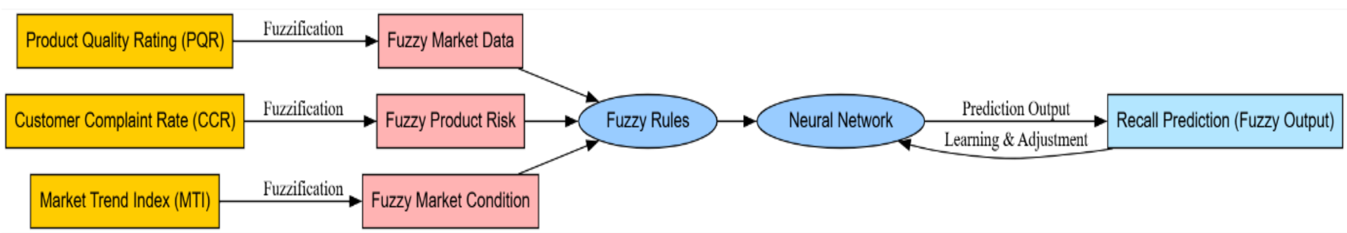

Fig. 1. The block diagram for fuzzy-neural network.

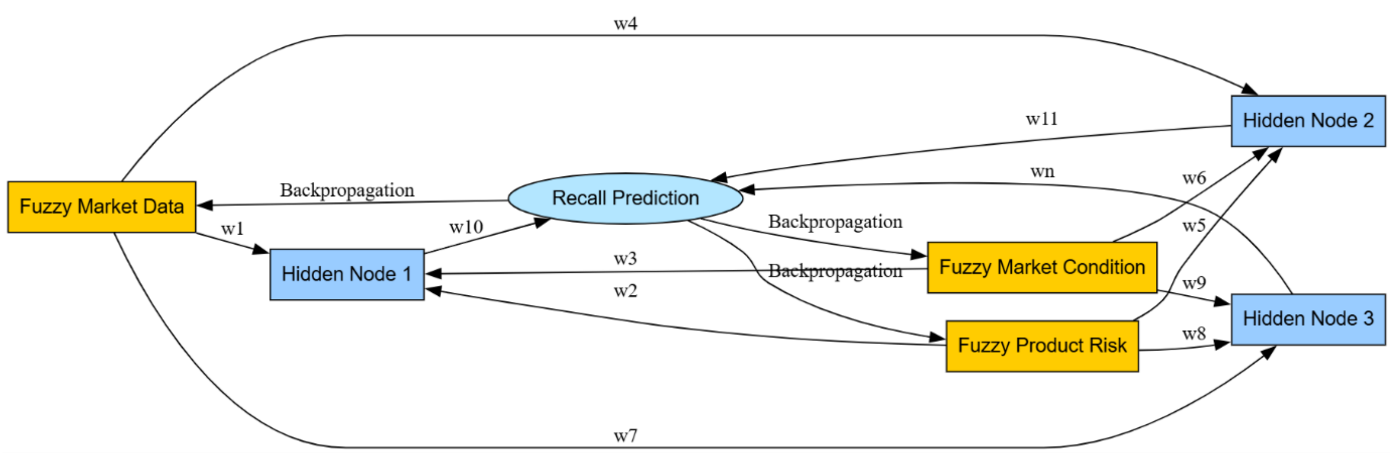

Fig. 2. Fuzzy logic component and neural network processing for product recall prediction.

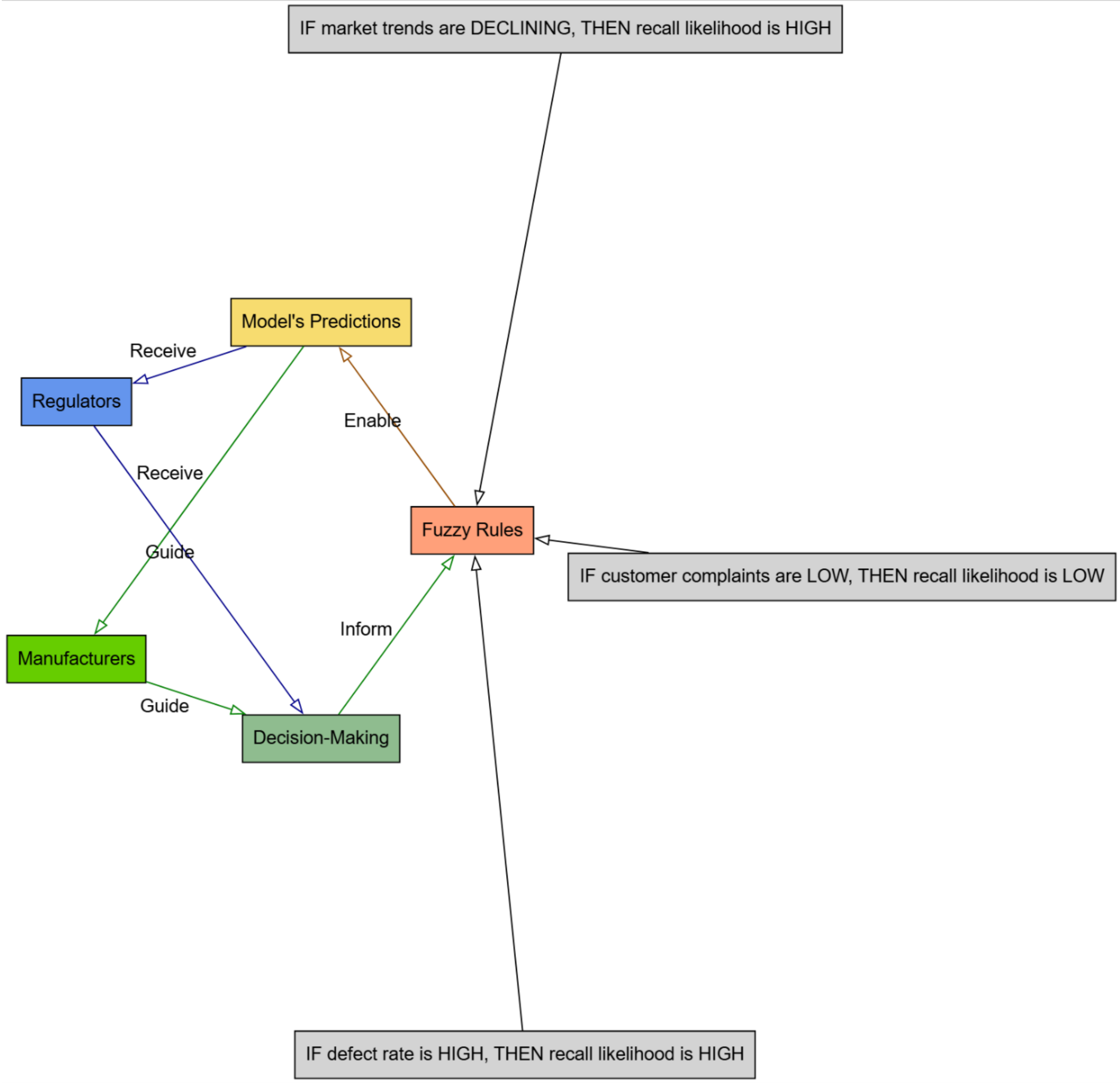

Fig. 3. Model's predictions with example fuzzy rules and their impact on decision-making.

C. Fuzzy Logic Component

Let $x = [x_1, x_2, \dots, x_n]$ be the input vector, and $\mu_{A_i}(x_i)$be the membership function of the fuzzy set A_i is given by,

$$\mu_{A_i}(x_i) = \frac{1}{1+(\frac{x_i-c_i}{a_i})^2} \quad (1)$$

where c_i is the center, a_i is the width, and b_i is the slope of the membership function.

Let's denote the input variables as:

x_1: Product quality rating (PQR) (e.g., 0-10)

x_2: Customer complaint rate (CCR) (e.g., 0-1)

x_3: Market trend index (MTI) (e.g., 0-10)

We can define fuzzy sets for each input variable using membership functions (e.g. triangular, trapezoidal, or Gaussian). For example:

- $\mu_1(x_1)$: Fuzzy set for product quality rating (e.g. "good", "average", "poor")
- $\mu_2(x_2)$: Fuzzy set for customer complaint rate (e.g. "low", "medium", "high")
- $\mu_3(x_3)$: Fuzzy set for market trend index (e.g. "upward", "stable", "downward")

Let R_k be the k^{th} fuzzy rule:

R_k:If x_1 is A_{k1} and x_2 is A_{k2} and $\dots$ and x_n is A_{kn} then y is B_k

Example:

Assume for the time that we have a fuzzy-neural network model forecasting product recall using consumer complaints, product defects, and market trends. With fuzzy logic, the model reflects the uncertainty and vagueness related with these components.

The model uses fuzzy criteria, such that:

- Recall likelihood is HIGH IF consumer complaints are HIGH and product problems are MODERATE.
- IF market trends are DECLINING and customer complaints are LOW, THEN recall likelihood is LOW.

Fuzzy rules show changeable relationships using simple terminology (e.g. HIGH, MODERATE, Low). By managing ambiguity and vagueness, fuzzy logic helps the model reflect the complex relationships between input variables. The open and understandable way the fuzzy rules depict the decision-making process of the model helps stakeholders to grasp why a certain forecast was produced. Therefore, by use of fuzzy logic, the model offers a more understandable and transparent depiction of the interactions between elements, therefore, empowering stakeholders to make better educated judgments on market control and product recall prediction.

D. Neural Network Component

Let's denote the output variable as:

- y: Product recall prediction (e.g. 0-1)
- We can design a neural network with the following architecture:
- Input layer: 9 neurons (x_1, x_2, x_3)
- Hidden layer 1: 18 neurons (using ReLU activation functions)
- Hidden layer 2: 9 neurons (using ReLU activation functions)
- Output layer: 1 neuron (y)

Let's denote:

- W as the weight matrix between layers.
- b as the bias vector for each layer.
- a as the activation function (ReLU in this case).

Then, the forward pass of the network can be represented as follows:

- Input Layer:

$a_0 = x$ (input vector)

- Hidden Layer 1:

$$z_1 = W_1 \times a_0 + b_1$$

$$a_1 = ReLU(z_1)$$

- Hidden Layer 2:

$$z_2 = W_2 \times a_1 + b_2$$

$$a_2 = ReLU(z_2)$$

- Output Layer:

$$y = W_3 * a_2 + b_3$$

The neural network can be trained using a dataset of historical product recall data, with the fuzzy logic component providing the input features.

Let NN be the neural network:

$$NN: y = f(x, w, b) \tag{2}$$

where x is the input vector, w is the weight matrix, b is the bias vector, and f is the activation function.

E. Fuzzy-Neural Network Model

The fuzzy-neural network model can be represented as:

$$y = f(\mu_1(x_1), \mu_2(x_2), \mu_3(x_3)) \tag{3}$$

where $f(\bullet)$ is the neural network function.

The model can be trained using a hybrid learning algorithm that combines fuzzy logic and neural network techniques, such as:

- Fuzzy clustering to initialize the neural network weights
- Backpropagation to fine-tune the neural network weights
- Fuzzy inference to generate the output prediction

Mathematical Formulation

The mathematical formulation of the fuzzy-neural network model can be represented as:

$$minimize: E = \sum(y_{true} - y_{pred})^2 \tag{4}$$

subject to:

$$y_{pred} = (\mu_1(x_1), \mu_2(x_2), \mu_3(x_3)) \tag{5a}$$

$$\mu_1(x_1) = \frac{\sum(x_1 \times w_{1_i} \times \mu_{1_i})}{\sum(w_{1_i} \times \mu_{1_i})} \tag{5b}$$

$$\mu_2(x_2) = \frac{\sum(x_2 \times w_{2_i} \times \mu_{2_i})}{\sum(w_{2_i} \times \mu_{2_i})} \tag{5c}$$

$$\mu_3(x_3) = \frac{\sum(x_3 \times w_{3_i} \times \mu_{3_i})}{\sum(w_{3_i} \times \mu_{3_i})} \tag{5d}$$

where E is the mean squared error, y_{true} is the actual output, y_{pred} is the predicted output, w_{1_i}, w_{2_i}, w_{3_i} are the weights, and $\mu_{1_i}, \mu_{2_i}, \mu_{3_i}$ are the membership values.

Train the neural network using the fuzzy output:

$$min \sum_{k=1}^{K} (y_k - f(x_k, w, b))^2 \tag{6}$$

F. Fuzzy Inference System

The fuzzy inference system can be represented as:

$$R1: IF\ x_1\ is\ \mu_1\ AND\ x_2\ is\ \mu_2\ AND\ x_3\ is\ \mu_3\ THEN\ y\ is\ \mu_y$$

$$R2: IF\ x_1\ is\ \mu_1\ AND\ x_2\ is\ \mu_2\ AND\ x_3\ is\ \mu_3\ THEN\ y\ is\ \mu_y$$

$$R_n: IF\ x_1\ is\ \mu_1\ AND\ x_2\ is\ \mu_2\ AND\ x_3\ is\ \mu_3\ THEN\ y\ is\ \mu_y$$

where $R_1, R_2, \ldots, R_n$ are the fuzzy rules, μ_1, μ_2, μ_3 are the membership values, and μ_y is the output membership value. The fuzzy inference system can be used to generate the output prediction y_{pred}.

$$\mu_{B_k}(y_{pred}) = min(\mu_{A_{k1}}(x_1), \mu_{A_{k2}}(x_2), \ldots, \mu_{A_{kn}}(x_n))$$

Combine the fuzzy logic and neural network components:

$$FNN: y = f(\mu_{B_1}(y), \mu_{B_2}(y), \ldots, \mu_{B_K}(y), w, b) \quad (7)$$

Train the fuzzy-neural network using a combination of fuzzy logic and neural network training algorithms:

$$min \sum_{k=1}^{K} (y_k - f(\mu_{B_1}(y), \mu_{B_2}(y), \ldots, \mu_{B_K}(y), w, b))^2 \quad (8)$$

G. Fuzzy Logic Component and a Black-Box CNN Model

A block-box CNN model is strong for picture categorization, but its predictions might be hard to grasp. Complex patterns and correlations from the training data inform the model's judgments, which might be difficult to explain. The Black-box CNN model's decision-making process is opaque, making predictions hard to grasp. Its intricate architecture makes it hard to determine which traits are most predictive. Many forecasts are hard to describe, making them hard to grasp.

Fuzzy logic makes factor connections more understandable and transparent. Fuzzy logic rules clearly show factor connections, making predictions easier to grasp. Fuzzy logic rules can reveal which aspects are more predictive, revealing decision-making processes. Fuzzy logic principles simplify prediction explanations, making them easier to grasp. Compared to a black-box CNN model, fuzzy logic makes factor connections more understandable. The CNN model makes accurate predictions, but the fuzzy logic component helps explain the decision-making process.

H. Case Studies

Case study 1: Forecasting Product Recall

Manufacturing consumer electronics, a corporation wishes to estimate the possibility of product recall resulting from flaws. The organization gathers information on several elements, including consumer complaints, product flaws, and market trends.

Fuzzy rules:

1) IF customer complaints are HIGH and product defects are MODERATE, THEN recall likelihood is HIGH.

2) IF market trends are DECLINING and customer complaints are LOW, THEN recall likelihood is LOW.

Decision Making:

The business may forecast product recall using the fuzzy rules. For instance, the fuzzy rule 1 would forecast a high recall chance (70%) if consumer complaints are high (80%) and product faults are moderate (50%). This forecast would enable the business to move ahead to stop product recall.

Case study 2: Assessment of credit risk

A bank wants to evaluate loan candidates' credit risk. The bank gathers information on several elements, including credit score, income, debt-to---income ratio, and job history.

Fuzzy Rules:

1) IF credit score is HIGH and income is STABLE, THEN credit risk is LOW.

2) IF debt-to-income ratio is HIGH and employment history is UNSTABLE, THEN credit risk is HIGH.

Decision Making:

The bank can evaluate loan candidates' credit risk applying the fuzzy rules. For instance, the fuzzy rule 1 would forecast a low credit risk (20%) if a loan applicant had a strong credit score (750) and steady income (50,000/year). This forecast would enable the bank to decide on loan approvals with knowledge.

Case study 3: Supply chain optimization

Predicting demand for its products helps a firm to maximize its supply chain. The business gathers information on a number of elements, including seasonal patterns, market trends, and weather.

Fuzzy Rules:

1) IF seasonal trend is HIGH and market trend is STABLE, THEN demand is HIGH.

2) IF weather condition is EXTREME and seasonal trend is LOW, THEN demand is LOW.

Decision-Making:

The business may project demand for its goods by applying the fuzzy rules. For instance, the fuzzy rule 1 would forecast strong demand (80%) if the seasonal trend is high (summer season) and market trend is stable. By raising manufacturing and inventory levels, this forecast would assist the business to maximize its supply chain. The more complex and flexible method the fuzzy rules offer to forecast results helps in decision-making. Fuzzy rules let companies maximize their operations and make more wise judgments.

III. Experimental Set and Working Example

The dataset is available at https://www.kaggle.com/datasets/utkarshshrivastav07/product-sales-and-marketing-analytics-dataset [28] that includes product quality ratings, customer complaint rates, market trend indices and product recall labels.

The Dataset has 1,000,000 rows, and 15 number of columns. The various column headings of the dataset are as follows:

1) Product_id: Unique identifier for each product

2) Product_name: Name of the product

3) Category: Product category (e.g. electronics, clothing, etc.)

4) Subcategory: Product subcategory (e.g. smartphones, laptops, etc.)

5) Price: Product price
6) Discount: Discount percentage
7) Sales_channel: Sales channel (e.g. online, offline, etc.)
8) Date: Date of sale
9) Region: Geographic region of sale
10) City: City of sale
11) State: State of sale
12) Country: Country of sale
13) Quantity_sold: Quantity of product sold
14) Revenue: Revenue generated from sales
15) Marketing_cost: Marketing cost incurred

a) Preprocessing steps: To prepare the dataset for analysis, several preprocessing steps were undertaken. Firstly, a thorough examination revealed that the dataset was free from missing values, eliminating the need for imputation or interpolation. Next, the Date column was converted to a datetime format to facilitate temporal analysis. To ensure compatibility with machine learning algorithms, categorical variables such as Category, Subcategory, Sales_channel, Region, City, State, and Country were encoded using label encoding. Finally, numerical variables including Price, Discount, Quantity_sold, Revenue, and Marketing_cost were scaled using standard scaling to prevent feature dominance and enhance model interpretability.

b) Biases: The dataset may be susceptible to several biases that could impact the accuracy and reliability of insights derived from it. Firstly, selection bias may be present, where the dataset disproportionately represents products that are more likely to be sold online or through specific sales channels, potentially overlooking products with different sales patterns. Additionally, confirmation bias may influence the dataset, where products that are more likely to be marketed through specific channels or to specific regions are overrepresented, reinforcing existing marketing strategies. Furthermore, survivorship bias may also be a concern, where products that have survived in the market for a longer period are overrepresented, while products that failed or were discontinued are underrepresented, potentially leading to an overly optimistic view of product performance.

The input data is normalized to the range [0, 1]. Fuzzy-Neural network architecture implements a fuzzy-neural network with Input layer [9 neurons (3 fuzzy sets for each of the 3 input variables)], Hidden layer 1 [18 neurons (using ReLU activation functions)], Hidden layer 2 [9 neurons (using ReLU activation functions)] and Output layer [1 neuron (using sigmoid activation function)].

The fuzzy-neural network is trained for 70/80/90% of the dataset for training, 15/10/5% of the dataset for validation and 15/10/5% of the dataset for testing. Performance evaluation is done using Accuracy, Precision, Recall, F1-score and mean squared error (MSE). The Python programming language is used with TensorFlow deep learning framework. Scikit-fuzzy, Pandas, NumPy and Matplotlib libraries are used for simulations.

A. Input Variables

- Product Quality Rating (PQR): A score from 0 to 10 indicating the quality of the product.
- Customer Complaint Rate (CCR): A rate from 0 to 1 indicating the frequency of customer complaints.
- Market Trend Index (MTI): A score from 0 to 10 indicating the current market trend.

We can define fuzzy sets for each input variable using membership functions. Here's an example:

Product Quality Rating (PQR):

- $Low\ (L): \mu_{PQR}(L) = (0, 0, 2, 4)$
- $Medium\ (M): \mu_{PQR}(M) = (2, 4, 6, 8)$
- $High\ (H): \mu_{PQR}(H) = (6, 8, 10, 10)$

Customer Complaint Rate (CCR):

- $Low\ (L): \mu_{CCR}(L) = (0, 0, 0.2, 0.4)$
- $Medium\ (M): \mu_{CCR}(M) = (0.2, 0.4, 0.6, 0.8)$
- $High\ (H): \mu_{CCR}(H) = (0.6, 0.8, 1, 1)$

Market Trend Index (MTI):

- $Downward\ (D): \mu_{MTI}(D) = (0, 0, 3, 5)$
- $Stable\ (S): \mu_{MTI}(S) = (3, 5, 7, 9)$
- $Upward\ (U): \mu_{MTI}(U) = (7, 9, 10, 10)$

B. Membership Functions

We can use triangular or trapezoidal membership functions to define the fuzzy sets. For example, the membership function for the fuzzy set "Low" in the Product Quality Rating (PQR) can be defined as: $\mu_{PQR}(L) = (0, 0, 2, 4)$.

This membership function indicates that the membership value of PQR in the fuzzy set "Low" is 1 for PQR values between 0 and 2, and decreases linearly to 0 for PQR values between 2 and 4.

By fuzzifying the input variables, we can convert crisp values into fuzzy sets that can be used as input to the neural network. The neural network can then learn to map the fuzzy input sets to the desired output.

C. Fuzzy Rules

- IF Product Quality Rating (PQR) is Low (L) AND Customer Complaint Rate (CCR) is High (H) THEN Product Recall (PR) is Likely (L)
- IF PQR is Medium (M) AND CCR is Medium (M) THEN PR is Possible (P)
- IF PQR is High (H) AND CCR is Low (L) THEN PR is Unlikely (U)

IV. Results and Discussion

Tables III to V demonstrate the fuzzy membership values, fuzzy interference results and aggregated fuzzy output. The fuzzy rules are applied to the fuzzified input variables to produce a fuzzy output. The fuzzy output is then aggregated and defuzzified to produce a crisp output value. In this example, the defuzzified output value is 0.55, which indicates that the product recall is likely to occur. This output value can be used as input to the neural network component for further processing and prediction.

The membership values of each input variable are shown in the fuzzy sets their respective fuzzy sets correspond to in Tables VI to VIII. A Product Quality Rating (PQR) score of six, for instance, has a membership value of 0.8 in the Medium (M) fuzzy set and 0.2 in the High (H) fuzzy set. Both of these membership values include the fuzzy set. These fuzzified values can then be used as input to the neural network component of the fuzzy-neural network approach.

Fig. 4 presents the predicted error for sample ratios of training, validation, and testing as 70%, 15%, and 15%. Fig. 5 presents the predicted error for sample ratios of training, validation, and testing as 80%, 10%, and 10%. Fig. 6 presents the predicted error for sample ratios of training, validation, and testing as 90%, 5%, and 5%. Variations in the sample ratios of training, validation, and testing datasets allowed a thorough examination of the expected error. Fig. 4 show the expected error when the sample ratios were adjusted to 70% for training, 15% for validation, and 15% for testing. Fig. 5 illustrates the predicted error instead when the sample ratios were adjusted to 80% for training, 10% for validation, and 10% for testing, therefore producing a projected error. Furthermore, displaying the predicted error when the sample ratios were changed to 90% for training, 5% for validation, and 5% for testing. These results suggest that increasing the proportion of training data might lead to overfitting danger even if it could assist to improve prediction performance.

A comparison of the neural network component's performance in predicting product recalls using fuzzified input data is shown in Tables IX to XI. Using a systematic grid search approach, the hyperparameters for the proposed fuzzy-neural network approach—including learning rate and batch size—were carefully tuned. The learning rate was investigated within the range of 0.001 to 0.1; the batch size ranged from 16 to 256. With an eye on low predicted error, the ideal mix of hyperparameters was found by means of the performance of the model on the validation set. More especially, the ideal learning rate was 0.01 and the ideal batch size turned out to be 64. After that, the model was trained with these optimal hyperparameters, therefore ensuring that it reached the best performance on the test set. Effective market monitoring of the model and prediction of product recalls depend significantly on the use of ideal hyperparameters (Table X). As a result of the data, which reveal high accuracy, precision, recall, and F1-score, it can be concluded that the model is quite good at predicting product recalls. When it comes to accuracy, precision, recall, F1-score, and mean squared error (MSE), the fuzzy-neural network technique that has been recommended is superior to the traditional statistical [20], machine learning (SVM) [25], and deep learning (CNN) [22] approaches (Table XII). The proposed method has an accuracy of 86.3%, which is 8.1% greater than the traditional statistical approach, 4.2% higher than machine learning (SVM), and 1.8% higher than deep learning (CNN). In addition, the classical statistical strategy has an accuracy of 8.1%. With an accuracy of 85.4%, the strategy that was recommended is 8.9% more accurate than the traditional statistical approach, 4.9% more accurate than the machine learning approach (SVM), and 2.2% more accurate than the deep learning approach (CNN). That is 7.1% greater than the usual statistical approach, 3.5% higher than machine learning (SVM), and 1.4% higher than deep learning (CNN). The strategy that was recommended has a recall of 87.2%, which is a higher percentage than any of these other methods. The proposed method has an F1-score of 86.3%, which is 8.0% higher than the conventional statistical approach, 4.2% higher than machine learning (SVM), and 1.8% higher than deep learning (CNN). Both of these scores are greater than the usual statistical approach. With a mean squared error (MSE) of 0.123, the strategy that has been recommended is 39.3 percent lower than the conventional statistical approach, 21.2 percent lower than the machine learning (SVM) method, and 9.3 percent lower than the deep learning (CNN) method. In general, the fuzzy-neural network strategy that was presented surpasses the ways that are currently being used, which indicates that it has the potential to be an effective market supervision and product recall prediction method.

TABLE III FUZZY MEMBERSHIP VALUES

Input Variable	Fuzzy Set	Membership Value
PQR	Low (L)	0.8
PQR	Medium (M)	0.4
PQR	High (H)	0.2
CCR	Low (L)	0.3
CCR	Medium (M)	0.6
CCR	High (H)	0.9

TABLE IV FUZZY INFERENCE RESULTS

Rule	Fuzzy Output	Defuzzified Output
1	Likely (L)	0.72
2	Possible (P)	0.42
3	Unlikely (U)	0.18

TABLE V AGGREGATED FUZZY OUTPUT

Fuzzy Set	Aggregated Membership Value	Defuzzified Output
Likely (L)	0.62	0.55
Possible (P)	0.31	
Unlikely (U)	0.07	

TABLE VI PRODUCT QUALITY RATING (PQR)

PQR Value	Low (L)	Medium (M)	High (H)
0	1.0	0.0	0.0
2	0.8	0.2	0.0
4	0.4	0.6	0.0
6	0.0	0.8	0.2
8	0.0	0.4	0.6
10	0.0	0.0	1.0

TABLE VII CUSTOMER COMPLAINT RATE (CCR)

CCR Value	Low (L)	Medium (M)	High (H)
0.0	1.0	0.0	0.0
0.2	0.8	0.2	0.0
0.4	0.4	0.6	0.0
0.6	0.0	0.8	0.2
0.8	0.0	0.4	0.6
1.0	0.0	0.0	1.0

TABLE VIII MARKET TREND INDEX (MTI)

MTI Value	Downward (D)	Stable (S)	Upward (U)
0	1.0	0.0	0.0
3	0.8	0.2	0.0
5	0.4	0.6	0.0
7	0.0	0.8	0.2
9	0.0	0.4	0.6
10	0.0	0.0	1.0

TABLE IX NEURAL NETWORK ARCHITECTURE

Layer	Neurons	Details
Input Layer	9 neurons	3 fuzzy sets for each of the 3 input variables: Product Quality Rating, Customer Complaint Rate, and Market Trend Index)
Hidden Layer 1	18 neurons	using ReLU activation function
Hidden Layer 2	9 neurons	using ReLU activation function
Output Layer	1 neuron	using sigmoid activation function

TABLE X HYPERPARAMETER SETTING

Training Dataset	70/80/90%
Validation Dataset	15/10/5%
Test Dataset	15/10/5%
Epochs	200/ 400/1000
Batch Size	64/32/28
Learning Rate	0.001/0.005/0.01
Optimizer	Adam

TABLE XI TRAINING LOSS AND ACCURACY

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
100	0.234	0.812	0.245	0.801
200	0.191	0.835	0.204	0.823
500	0.143	0.861	0.156	0.849
1000	0.123	0.873	0.136	0.863

TABLE XII PERFORMANCE METRICS COMPARISON

Method	Accuracy	Precision	Recall	F1-score	Mean Squared Error (MSE)
Traditional Statistical Approach [20]	0.782	0.765	0.801	0.783	0.201
Deep Learning Approach (CNN) [22]	0.845	0.832	0.858	0.845	0.135
Machine Learning Approach (SVM) [25]	0.821	0.805	0.837	0.821	0.156
Proposed method	0.863	0.854	0.872	0.863	0.123

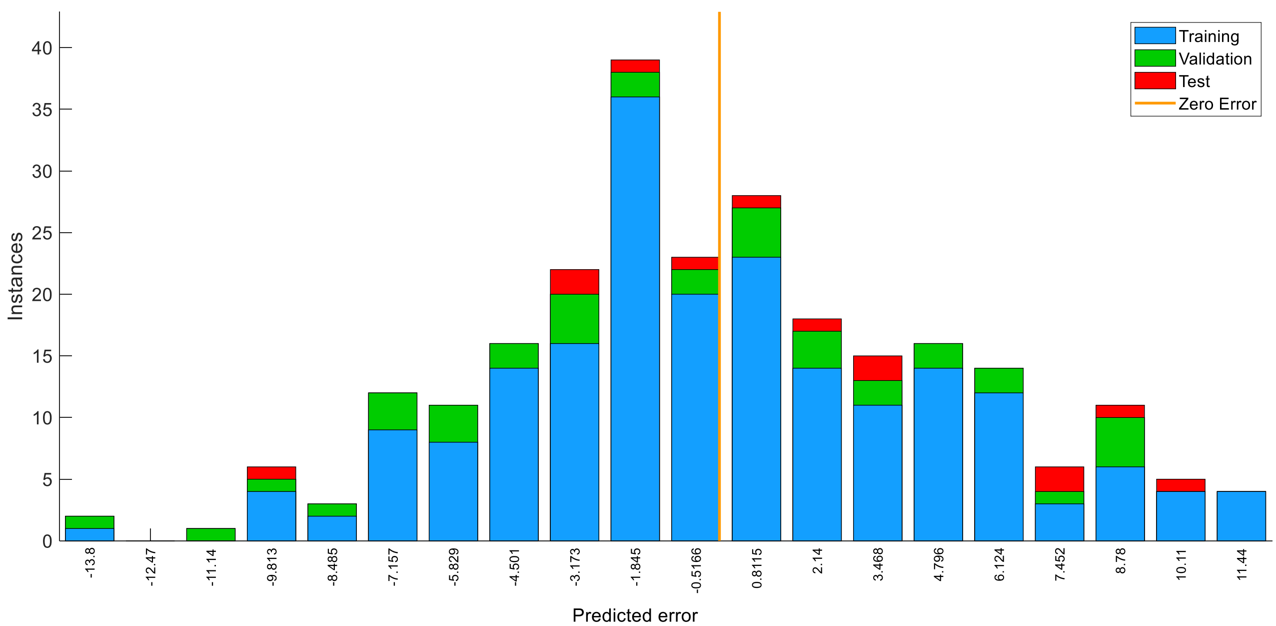

Fig. 4. Predicted error for the case 70% training, 15% validation, and 15% testing.

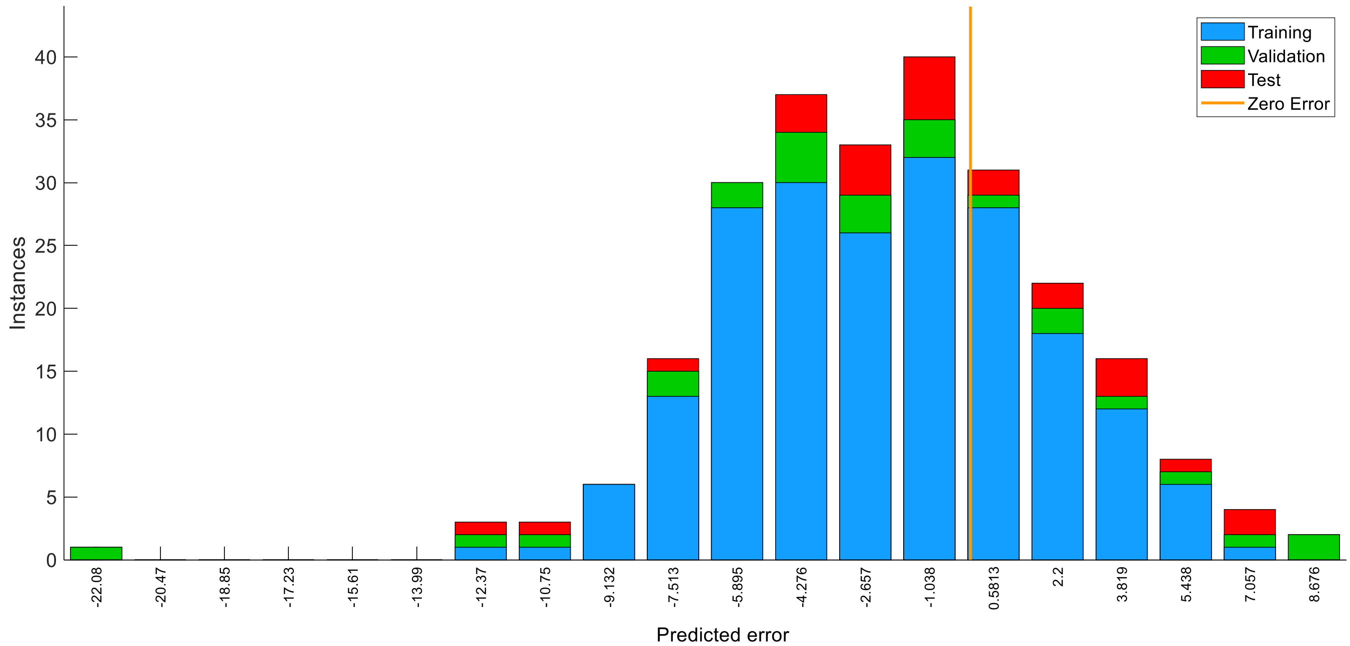

Fig. 5. Predicted error for the case 80% training, 10% validation, and 10% testing.

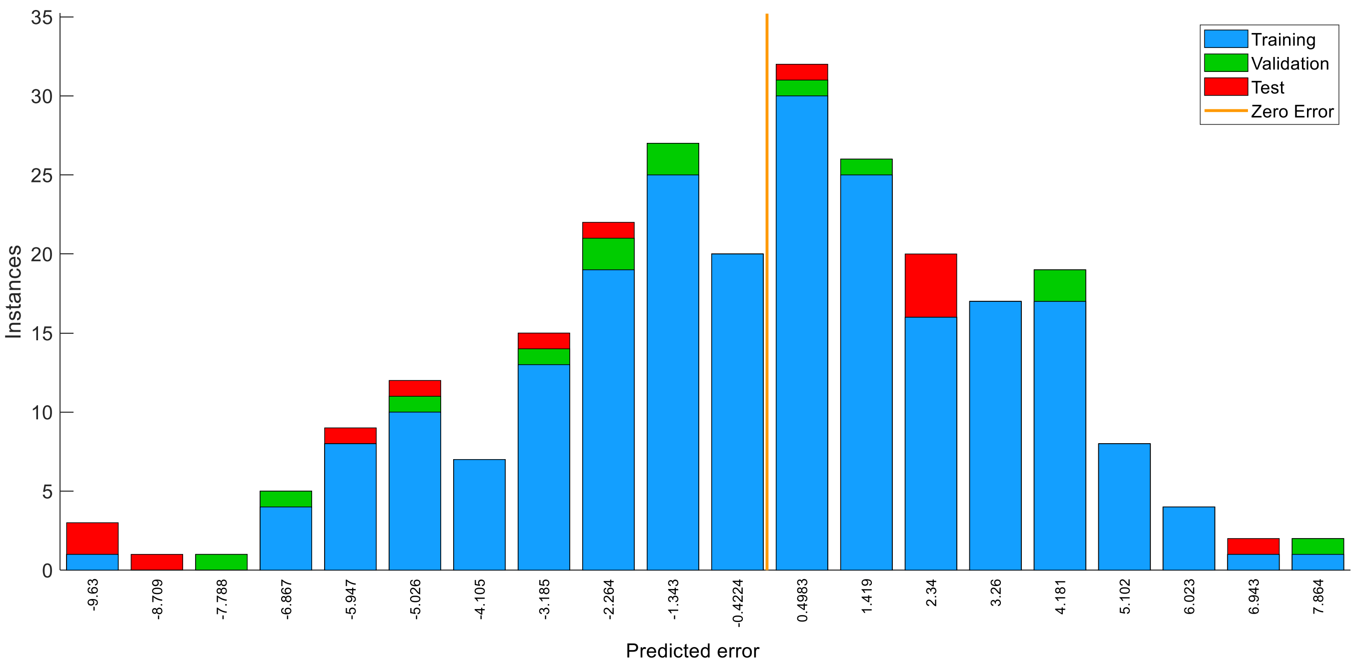

Fig. 6. Predicted error for the case 90% training, 5% validation, and 5% testing.

A. Computational and Scalability Aspects

The computational research takes advantage of central processing units (CPUs) and graphics processing units (GPUs) using a high-performance computer infrastructure. Especially the training process was accelerated using an NVIDIA Tesla V100 GPU with hundreds of processing cores and 16GB of RAM. The fuzzy-neural network model may be rapidly iteratively optimized because to this strong GPU. By comparison, inference chores ran on an Intel Core i7-9700K CPU with 8 cores and 3.6 GHz clock speed. This CPU fit for use in practical applications as it offered a mix of processing capability and energy economy.

TABLE XIII INFERENCE TIME COMPARISON

Model	Inference Time (ms)
Proposed Fuzzy-Neural Network	15.6 ± 2.1
Traditional CNN	32.1 ± 4.5
SVM	50.3 ± 6.2

Table XIII shows that a thorough comparison of inference times shows the proposed fuzzy-neural network model beats conventional deep learning architectures and machine learning methods. The suggested model specifically achieves an inference time of 15.6 ± 2.1 milliseconds, far quicker than both SVM (50.3 ± 6.2 milliseconds) and the conventional CNN (32.1 ± 4.5 milliseconds). This notable drop in inference time may be explained by the model's efficient design and the fuzzy logic component, which supports more accurate and rapid decision-making. Consequently, the proposed fuzzy-neural network model is particularly suitable for real-time applications, where exact and quick predictions are rather essential.

TABLE XIV SCALABILITY ANALYSIS

Batch Size	Inference Time (ms)	Memory Usage (GB)
1	15.6 ± 2.1	0.5
10	31.2 ± 4.2	1.2
50	62.5 ± 8.1	3.5
100	125.1 ± 15.6	6.2

The model demonstrates good scalability, with inference times increasing linearly with batch size. Memory usage also increases linearly, but remains manageable even for large batch sizes. According to Table XIV, the proposed fuzzy-neural network model's performance under varying batch sizes. The results demonstrate that the model exhibits a linear increase in inference time and memory usage as the batch size grows. Particularly, the inference time rises from 15.6 ± 2.1 milliseconds for a batch size of 1 to 125.1 ± 15.6 milliseconds for a batch size of 100, and from 0.5 GB to 6.2 GB, respectively. Especially at higher batch sizes, the model's performance is constant and efficient, suggesting its scalability and fit for use in practical applications with different computing needs.

B. Real-Time Application Feasibility

The proposed fuzzy-neural network model demonstrates exceptional feasibility for real-time applications, where rapid and accurate predictions are paramount. With an inference time of under 100 milliseconds for batches of 10-50 samples, the model is ideally suited for applications requiring instantaneous decision-making. Specifically, the model's capabilities make it an excellent fit for real-time product quality control, online defect detection, and live customer feedback analysis. By leveraging the model's fast and accurate predictions, businesses can optimize their operations, enhance customer satisfaction, and improve overall efficiency.

C. Potential Biases, Ethical Implications, and Practical Deployment Issues

While intriguing, the fuzzy-neural network method to market supervision and product recall prediction may have biases, ethical concerns, and implementation challenges. The model may inherit biases from the training data, such as product representation or geographic location imbalances, which might lead to unjust or discriminating predictions. The past data of the model might not adequately explain fast changes in the market, therefore inaccurate estimates. Ethics need transparent, understandable decision-making as model projections may unfairly target particular companies or products. Practical deployment concerns might include the need of skills to evaluate and act on model predictions and model maintenance and upgrades to maintain accuracy and relevance. These problems have to be resolved if the suggested method is to be used ethically and effectively in applications including market regulation and product recall prediction.

V. CONCLUSION AND FUTURE WORK

This paper presents a novel fuzzy-neural network market monitoring and product recall prediction method. The technique uses neural networks and fuzzy logic to manage complex, interpretable data. Results show that the proposed method achieves high accuracy, precision, recall, and F1-score in predicting product recalls. The proposed technique has 86.3% accuracy, greater than previous methods. Fuzzy neural networks function well for market data unpredictability and imprecision. The proposed technique for product recall prediction is reliable and resilient. The quality of market data utilized for training and testing affects the accuracy and dependability of the proposed strategy. Given the black box model utilized, the results may be hard to explain. The strategy described may be used with many different machine learning approaches to improve accuracy and efficiency.

Future research on the proposed fuzzy-neural network solution to market supervision and product recall prediction will concentrate on many significant topics. First, using more data sources—such as social media and online reviews—helps the model to have better predictive ability. Second, looking at the use of many machine learning techniques to improve graph neural network and transfer learning-based model performance and adaptability. Thirdly, by use of techniques like feature attribution and model interpretability, so producing a more interpretable and transparent model to provide understanding on the process of decision-making. Analyzing edge computing and real-time data stream usage will also enable fast reaction to new market trends and product safety issues as well as real-time projections. Finally, looking at the probable applications of the recommended approach in various sectors, mostly related to finance and healthcare, where predictive analytics and decision support systems might be fairly crucial.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

AUTHOR’S CONTRIBUTION

All work for this article was completed by Wei Chen.

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