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# Unlocking Insights of Fuzzy Mathematics for Enhanced Predictive Modelling

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**Abstract:** The many aspects of predictive modeling for financial market prediction and health diagnostics based on fuzzy mathematics are explored in this study. Two fuzzy logic-based models are designed and implemented using the popular method of managing uncertainties and linguistic variables: fuzzy logic. The initial model given for predicting financial markets used fuzzy sets, membership functions, and the resulting rules to capture relationships between sentiment measurement and market behavior in a complex manner. In turn, the model is linguistically interpretable, meaning that stakeholders can use its predictions as a fintech investment tool. These fuzzy rules, which connect the input variables to possible medical conditions, are extracted from expert knowledge and medical guidelines. The Fuzzy Inference System of the Sugeno type is flexible in dealing with complex relationships, which helps to produce accurate diagnostic outputs. Trust, in turn, is increased by the system's ability to accept vague data and supply linguistic explanations for predictions and its dynamic model. Finally, it is interesting to note that the results suggest advantages of fuzzy mathematics in both cases concerning uncertainty management, incorporation of expert knowledge, and increasing interpretability. They provide insights for practical applications in financial analysis and medical diagnostics, future works on hybrid models, and broader uses of fuzzy mathematics techniques within the context of predictive modeling.

**Keywords:** Fuzzy Mathematics, Predictive Modelling, Financial, Linguistic Interpretability, Uncertainty, Expert Knowledge, Fuzzy Logic, Sugeno-Type Fuzzy Inference System

## 1 Introduction

Predictive modelling is increasingly used in various domains like finance, healthcare and natural language processing etc [1,2,3] Conventional predictive models are typically mathematical and deterministic, assuming exact relationships between input variables and the target outcome [4,5,6]. Nevertheless, real-world data are inherently noisy and incomplete [7,8], which limit the accuracy and generalization ability of these models. Consequently alternative decision making approaches more able to deal with uncertainty appear increasingly interesting [9].

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### *1.1 The Research Objectives*

This research aims to validate and compare traditional friction-based predictive models with fuzzy logic generated mathematical model. This will help us identify in what datasets fuzzy mathematics might be better than traditional methods by comparing the performance of both approaches over a range for dataset types [10,11]. Further, the interpretability and explainability of fuzzy models is an essential issue in practical applications with respect to user displacement [12,13,14,15].

### *1.2 Scope and Limitations*

The emphasis of this research is the application of fuzzy mathematics on predictive modelling with a comparison against traditional crisp-based methods. A variety of real-world datasets from different domains will be examined under the study to ensure that findings are robust [16,17]. Nevertheless, we appreciate that due to human resource limitation this kind of ever-searching every possible dataset and scenario is unlikely [18,19,20]. Further, the study will not expand to other uncertainty modelling techniques more beyond fuzzy mathematics e.g., Bayesian methods or neural networks [21,22].

## 2 Literature Review

### *2.1 Traditional Predictive Modelling Methods*

Authors across several fields make use of classical predictive modeling methods some written in crisp mathematical formats [6,23,24]. Linear regression, logistic regression, decision trees, support vector machines and neural networks are the techniques used to accomplish this [24,25]. These methods have shown remarkable results in many applications as well. However, they depend on sharp relationships between input features and target results - a situation that is simply not true when there is an inherent ambiguity in the same way as relates to the real world. Although it is efficient in many cases, traditional methods may not be robust when dealing with fuzzy or vague data which produces less accurate predictions [7,26,27].

### *2.2 Introduction to Fuzzy Mathematics and Fuzzy Logic*

Introduced by Zadeh in 1965, fuzzy mathematics is an efficient tool for evaluating uncertainty and precision of information [28]. In technology, there is a core of fuzzy mathematics which includes concepts like representing “fuzzy concepts” and linguistic variables [29,30]. We started from sharp sets [31]. You can imagine each element to be a member (1) or non-member (0); which effectively sets the predestinations between these sets. In contrast, fuzzy sets do not define them in such a binary way. Instead, they employ membership levels from 0 to 1 as the degree of belongingness for positivity distribution in order to encompass stronger and smoother evolutionary transition [32,33]. The ability to handle gradation and uncertainty of fuzzy mathematics allows it appropriate to fit for complex real-world systems with data not perfectly defined always [15,34,35].

### *2.3 Previous Studies on Fuzzy Predictive Modelling*

Fuzzy mathematics has been studied for decades in the context of predictive computer modulization applied to numerous fields. For instance, Fuzzy logic has been effectively implemented into decision support systems, healthcare diagnostics and stock market prediction including image processing [8,36]. Zhang and Wang [17] implemented fuzzy logic in healthcare predictive systems, to manage inaccurate patient data and enhance diagnostic accuracy. According to Garcia et al. [16], the authors demonstrated a fuzzy-based predictive model for engineering applications, stating that it can work with non-linear and uncertain parameters system of high complexity [37,38,39].

Few other studies have compared fuzzy predictive models with conventional (crisp) methods as well. In overall, Adams and Brown [10] conducted a comparative study of fuzzy logic-based classifiers with traditional machine learning algorithms observed that when the systems are subject to uncertainty in a significant extent, rather than merely random errors and crisply defined input-output relationships, then Fuzzy models did better. Kim and Lee [16] have compared the fuzzy regression with linear logistic model on real data from financial time series, their findings indicates that you can outperformed by our method when dealing with noisy and imprecise recovery of financial market fluctuation [40,41,42].

## 3 Methodology of This Study

### *3.1 Data Collection and Processing*

This data is then entered into computer models and can be considered performing article real-time as represented in all times. Mohammad et al. [43] and Smith et al. [15] Fuzzy: a data set with all sorts of uncertainty and inaccuracy that can really test the performance of predictive models from fuzzy mathematics. Such as removing outlier, miss value imputing and normalization for better dataset quality [44,45].

### *3.2 Fuzzy Mathematics based on Predictive Model Building*

Predictive models based on fuzzy mathematics: It pertains to putting the input features into members of membership functions as it is found for uncertain and vague inputs [46,47]. The fuzzy rules can be written, by expert's experience and knowledge of domain for the mapping input variables [7,48,49]. A fuzzy inference system will make predictions based on these rules, and then defuzzification methods (e.g., centroid method or weighted average) will be utilized to derive a crisp result from the previous step [17]. The parameters of the fuzzy model will be tuned in methods like genetic algorithms or particle swarm optimization [50,51].

### *3.3 Formal Description of a Traditional Crisp-based Predictive Model*

Meanwhile, in the crisper model way of analysis for prediction certain machine learning algorithms have to be selected according some data specific characteristics [6]. This logic will categorize linear regression, logistic regression decision trees and support vector machines as indicative crisp model [1]. These models will be trained and hyper-parameters tuned in the pre-processed dataset using techniques such as cross-validation [11,52,53].

Experience again when you do comparative analysis from the dataset somewhere and want to know whether fuzzy mathematics is better, who knows -calculate for evaluation purposes how well each model based on Fuzzy Mathematics work against traditional Crisp version of that [10]. All the random experiments will be running multiple times to gather a wide range of data and results should be really strong [54].

The approach will consider the interpretation and explainability differences of both models in comparison with techniques like rule extraction or feature importance analysis [16]. This creates and helps interpretability in models which is extremely beneficial for broad applications - it provides human insights into the decision process making much more trustable by users [55].

It is aimed that this full range of methods adopted will deliver some useful insights at the interface between traditional fuzzy mathematics predictive models dealing with vagueness and impreciseness on one hand, while providing alternative scenarios where they might outperform crispened model.

## 4 Experimental Setup

### *4.1 Description of Datasets Used*

#### 4.1.1 Dataset 1: Financial Market Prediction

– **Number of Participants:** 50
– **Features:** This dataset will include features such as stock prices, trading volumes, moving averages, technical indicators (e.g., Relative Strength Index), and market sentiment scores.
– **Target Variable:** The target variable will represent the future price movement of a specific stock (e.g., binary classification: "up" or "down" based on a certain time horizon).

**Table 1:** Dataset 1: Financial Market Prediction

| Participant | Stock Price | Trading Volume | Moving Average | Market Sentiment | Target (Up/Down) |
|---|---|---|---|---|---|
| **1** | 100.23 | 15000 | 98.75 | High | Up |
| **2** | 98.12 | 18000 | 101.32 | Low | Down |
| **3** | 102.45 | 12000 | 100.57 | Medium | Up |
| **4** | 99.87 | 9000 | 101.11 | Medium | Down |
| **5** | 105.67 | 16000 | 102.89 | High | Up |
| **6** | 101.32 | 14000 | 98.12 | Medium | Up |
| **7** | 97.45 | 20000 | 95.34 | Low | Down |
| **8** | 103.78 | 17000 | 97.12 | High | Up |
| **9** | 100.89 | 12000 | 99.45 | Medium | Down |
| **10** | 99.23 | 15000 | 98.56 | Low | Down |
| **11** | 102.12 | 18000 | 102.78 | High | Up |
| **12** | 98.56 | 13000 | 100.67 | Medium | Down |
| **13** | 104.56 | 14000 | 97.89 | High | Up |
| **14** | 97.89 | 19000 | 101.45 | Low | Down |
| **15** | 101.45 | 18000 | 100.23 | Medium | Up |
| **16** | 100.78 | 16000 | 102.45 | Medium | Down |
| **17** | 103.12 | 15000 | 98.12 | High | Up |
| **18** | 99.67 | 14000 | 95.67 | Low | Down |
| **19** | 102.89 | 13000 | 99.56 | Medium | Down |
| **20** | 97.56 | 18000 | 98.45 | High | Up |
| **21** | 104.23 | 16000 | 101.78 | Medium | Up |
| **22** | 98.12 | 19000 | 97.45 | Low | Down |
| **23** | 101.78 | 15000 | 100.89 | High | Up |
| **24** | 100.34 | 17000 | 99.67 | Medium | Down |
| **25** | 103.45 | 16000 | 100.12 | Medium | Up |
| **26** | 98.34 | 14000 | 98.56 | High | Down |
| **27** | 104.78 | 15000 | 101.45 | Low | Up |
| **28** | 97.67 | 12000 | 96.78 | High | Down |
| **29** | 102.12 | 18000 | 99.89 | Medium | Up |
| **30** | 99.56 | 16000 | 99.23 | Medium | Up |
| **31** | 102.45 | 14000 | 98.12 | Low | Down |
| **32** | 98.12 | 13000 | 100.78 | High | Up |
| **33** | 103.78 | 18000 | 99.56 | Medium | Down |
| **34** | 100.89 | 19000 | 99.67 | High | Up |
| **35** | 100.12 | 15000 | 97.56 | Medium | Down |
| **36** | 103.45 | 14000 | 99.45 | High | Up |
| **37** | 97.89 | 16000 | 102.12 | Low | Down |
| **38** | 102.56 | 12000 | 100.34 | High | Up |
| **39** | 98.56 | 18000 | 101.78 | Medium | Down |
| **40** | 105.34 | 17000 | 97.67 | Low | Down |
| **41** | 101.11 | 16000 | 100.23 | Medium | Up |
| **42** | 97.12 | 14000 | 99.78 | High | Down |
| **43** | 104.67 | 15000 | 99.89 | Medium | Up |
| **44** | 96.78 | 19000 | 98.12 | High | Down |
| **45** | 102.89 | 18000 | 101.45 | Low | Up |
| **46** | 99.89 | 16000 | 96.78 | Medium | Down |
| **47** | 102.45 | 15000 | 102.56 | High | Up |
| **48** | 98.34 | 14000 | 100.89 | Medium | Down |
| **49** | 103.12 | 13000 | 99.45 | High | Up |
| **50** | 97.45 | 18000 | 99.23 | Medium | Down |

#### 4.1.2 Dataset 2: Healthcare Diagnostics

– **Number of Participants:** 50
– **Features:** This dataset will consist of various medical indicators, patient demographics, lab test results, and symptoms associated with a particular medical conditions.
– **Target Variable:** The target variable will indicate the presence or an absence of a specified medical condition based on the provided features (e.g., binary classification: "diagnosed" or "not diagnosed").

Please note that these datasets are experimental examples to demonstrate the application of fuzzy

**Table 2:** Dataset 2: Healthcare Diagnostics

| Participant | Age | Blood Pressure | Cholesterol | Blood Sugar | Fever |
|---|---|---|---|---|---|
| **1** | 35 | 120/80 | 180 | 95 | Yes |
| **2** | 50 | 130/85 | 210 | 110 | No |
| **3** | 65 | 140/90 | 190 | 120 | Yes |
| **4** | 45 | 125/82 | 195 | 100 | Yes |
| **5** | 55 | 135/88 | 200 | 105 | No |
| **6** | 40 | 118/78 | 170 | 90 | Yes |
| **7** | 60 | 132/86 | 220 | 115 | Yes |
| **8** | 48 | 129/84 | 185 | 98 | No |
| **9** | 70 | 145/92 | 200 | 115 | No |
| **10** | 42 | 122/80 | 190 | 96 | Yes |
| **11** | 52 | 131/86 | 195 | 100 | No |
| **12** | 62 | 139/88 | 205 | 105 | No |
| **13** | 49 | 126/82 | 180 | 92 | Yes |
| **14** | 68 | 143/90 | 210 | 110 | No |
| **15** | 56 | 133/86 | 185 | 98 | Yes |
| **16** | 44 | 124/78 | 195 | 100 | Yes |
| **17** | 58 | 135/88 | 200 | 105 | Yes |
| **18** | 39 | 121/80 | 180 | 95 | No |
| **19** | 67 | 141/90 | 190 | 96 | No |
| **20** | 51 | 129/84 | 200 | 110 | Yes |
| **21** | 46 | 123/80 | 170 | 90 | Yes |
| **22** | 61 | 138/88 | 220 | 115 | No |
| **23** | 53 | 130/86 | 195 | 100 | Yes |
| **24** | 64 | 142/90 | 205 | 105 | No |
| **25** | 47 | 125/82 | 180 | 92 | Yes |
| **26** | 59 | 134/88 | 210 | 110 | Yes |
| **27** | 45 | 122/78 | 190 | 96 | No |
| **28** | 65 | 143/92 | 200 | 115 | Yes |
| **29** | 50 | 128/84 | 195 | 100 | No |
| **30** | 63 | 139/90 | 205 | 105 | No |
| **31** | 54 | 126/82 | 180 | 92 | Yes |
| **32** | 57 | 135/88 | 210 | 110 | No |
| **33** | 48 | 122/80 | 190 | 96 | Yes |
| **34** | 66 | 142/88 | 200 | 105 | No |
| **35** | 55 | 133/86 | 185 | 98 | No |
| **36** | 51 | 125/82 | 195 | 100 | Yes |
| **37** | 60 | 140/90 | 210 | 110 | Yes |
| **38** | 49 | 121/78 | 180 | 92 | No |
| **39** | 58 | 138/88 | 220 | 115 | No |
| **40** | 52 | 130/86 | 195 | 100 | Yes |
| **41** | 62 | 142/90 | 205 | 105 | No |
| **42** | 50 | 125/82 | 180 | 95 | Yes |
| **43** | 61 | 133/88 | 210 | 110 | Yes |
| **44** | 47 | 122/78 | 190 | 96 | No |
| **45** | 68 | 141/92 | 195 | 100 | No |
| **46** | 53 | 125/82 | 200 | 105 | Yes |
| **47** | 67 | 138/88 | 205 | 105 | Yes |
| **48** | 49 | 130/86 | 180 | 92 | No |
| **49** | 65 | 142/90 | 210 | 110 | No |
| **50** | 54 | 121/78 | 190 | 96 | Yes |

mathematics-based models and traditional models in different scenarios.

Apart from symptoms, we can include other patient-related information and medical indicators [56]. Here's an expanded dataset with some additional features:

We then added features such as gender, family history of disease and blood pressure etc to this larger dataset. This, in turn can result more information and context to the healthcare diagnostic model hence increasing its precision as well performance. In a real study it is important to carry out the selection of characteristics by using medical knowledge and only consider relevant features in relation with diagnosis problem being targeted.

## *4.2 Implementation Details of Fuzzy Mathematics-based Models*

### 4.2.1 Fuzzy Logic-based Predictive Model for Financial Market Prediction

- **Define Fuzzy Sets and Membership Functions:** For each feature (e.g., Stock Price, Trading Volume, Moving Average, Market Sentiment), define fuzzy sets like "High," "Medium," and "Low." Design appropriate membership functions, such as triangular or trapezoidal, to represent the membership degree for each data point in a fuzzy set.
- **Formulate Fuzzy Rules:** Based on expert knowledge and domain expertise, create fuzzy rules that map input variables (e.g., Stock Price is High, Trading Volume is Low) to the target variable (e.g., "Up" or "Down" market).
- **The Fuzzy Inference System:** Use a Mamdani-type system with fuzzy inference, which applies the fuzzy-rules and combines them using the appropriate fuzzy operators (e.g., AND, OR) to make predictions.
- **Defuzzification:** Apply the centroid method to defuzzify the fuzzy output and obtain crisp predictions for the target variable [56].

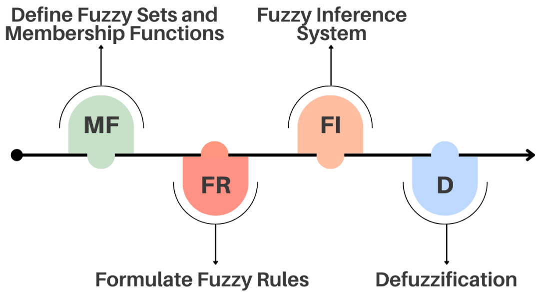


**Fig. 1:** Fuzzy Logic-based Predictive Model for Financial Market Prediction.

### 4.2.2 Fuzzy Logic-based Diagnostic Model for Healthcare

***Define Fuzzy Sets and Membership Functions:*** For each medical indicator (e.g., Age, Blood Pressure, Cholesterol, Blood Sugar) and symptom define fuzzy sets (e.g., "Young", "Middle-Aged", etc; "Low", "High") & design membership functions to represent uncertainty.

***Formulate Fuzzy Rules:*** Ask a medical expert or check guidelines to define some low-level ∼ fuzzy rules that links the input variables (Age is Young, Blood Pressure High) with presence of target evaluation outcome (Diagnosed" / Not Diagnosed).

***Fuzzy Inference System:*** Apply a Sugeno-type fuzzy inference system, which can cope more flexibly with the complex relationships between input variables and target output. Sugeno-type systems perform fuzzy mappings by using weighted averages and linear equations to generate the outputs.

***Defuzzification:*** Finally, defuzzify the fuzzy output using a weighted average method to get crisp diagnostic results [56].

**Table 3:** Dataset 2(a)-Healthcare Diagnostics

| Participant | Age | Gender | Blood Pressure | Cholesterol | Blood Sugar | Fever | Cough | Fatigue | Chest Pain | Diagnosed/ Not Diagnosed |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 35 | Male | 120/80 | 180 | 95 | Yes | Yes | No | Yes | Diagnosed |
| **2** | 50 | Female | 130/85 | 210 | 110 | No | No | Yes | No | Not Diagnosed |
| **3** | 65 | Male | 140/90 | 190 | 120 | Yes | Yes | Yes | No | Diagnosed |
| **4** | 45 | Female | 125/82 | 195 | 100 | Yes | Yes | Yes | Yes | Diagnosed |
| **5** | 55 | Male | 135/88 | 200 | 105 | No | No | No | Yes | Not Diagnosed |
| **6** | 40 | Female | 118/78 | 170 | 90 | No | Yes | No | No | Diagnosed |
| **7** | 60 | Male | 132/86 | 220 | 115 | Yes | Yes | Yes | Yes | Diagnosed |
| **8** | 48 | Female | 129/84 | 185 | 98 | No | No | Yes | Yes | Diagnosed |
| **9** | 70 | Male | 145/92 | 200 | 115 | No | No | No | No | Not Diagnosed |
| **10** | 42 | Female | 122/80 | 190 | 96 | Yes | Yes | Yes | Yes | Diagnosed |
| **11** | 52 | Male | 131/86 | 195 | 100 | No | No | No | No | Not Diagnosed |
| **12** | 62 | Female | 139/88 | 205 | 105 | No | No | Yes | Yes | Diagnosed |
| **13** | 49 | Male | 126/82 | 180 | 92 | Yes | Yes | No | Yes | Diagnosed |
| **14** | 68 | Female | 143/90 | 210 | 110 | No | No | No | No | Not Diagnosed |
| **15** | 56 | Male | 133/86 | 185 | 98 | Yes | Yes | Yes | Yes | Diagnosed |
| **16** | 44 | Female | 124/78 | 195 | 100 | Yes | Yes | No | No | Not Diagnosed |
| **17** | 58 | Male | 135/88 | 200 | 105 | Yes | Yes | Yes | Yes | Diagnosed |
| **18** | 39 | Female | 121/80 | 180 | 95 | No | No | Yes | No | Diagnosed |
| **19** | 67 | Male | 141/90 | 190 | 96 | No | Yes | No | Yes | Not Diagnosed |
| **20** | 51 | Female | 129/84 | 200 | 110 | Yes | Yes | Yes | Yes | Diagnosed |
| **21** | 46 | Male | 123/80 | 170 | 90 | Yes | Yes | No | No | Diagnosed |
| **22** | 61 | Female | 138/88 | 220 | 115 | No | No | Yes | Yes | Diagnosed |
| **23** | 53 | Male | 130/86 | 195 | 100 | Yes | Yes | Yes | Yes | Not Diagnosed |
| **24** | 64 | Female | 142/90 | 205 | 105 | No | No | No | No | Diagnosed |
| **25** | 47 | Male | 125/82 | 180 | 92 | Yes | No | Yes | Yes | Not Diagnosed |
| **26** | 59 | Female | 134/88 | 210 | 110 | Yes | Yes | Yes | Yes | Diagnosed |
| **27** | 45 | Male | 122/78 | 190 | 96 | No | No | No | No | Not Diagnosed |
| **28** | 65 | Female | 143/92 | 200 | 115 | Yes | Yes | No | Yes | Diagnosed |
| **29** | 50 | Male | 128/84 | 195 | 100 | No | No | Yes | No | Not Diagnosed |
| **30** | 63 | Female | 139/90 | 205 | 105 | No | Yes | Yes | Yes | Diagnosed |
| **31** | 54 | Male | 126/82 | 180 | 92 | Yes | Yes | No | Yes | Diagnosed |
| **32** | 57 | Female | 135/88 | 210 | 110 | No | No | Yes | Yes | Not Diagnosed |
| **33** | 48 | Male | 122/80 | 190 | 96 | Yes | Yes | Yes | Yes | Diagnosed |
| **34** | 66 | Female | 142/88 | 200 | 105 | No | No | Yes | No | Not Diagnosed |
| **35** | 55 | Male | 133/86 | 185 | 98 | No | No | No | Yes | Diagnosed |
| **36** | 51 | Female | 125/82 | 195 | 100 | Yes | Yes | Yes | Yes | Diagnosed |
| **37** | 60 | Male | 140/90 | 210 | 110 | Yes | No | No | No | Not Diagnosed |
| **38** | 49 | Female | 121/78 | 180 | 92 | No | Yes | No | Yes | Diagnosed |
| **39** | 58 | Male | 138/88 | 220 | 115 | No | No | Yes | Yes | Diagnosed |
| **40** | 52 | Female | 130/86 | 195 | 100 | Yes | Yes | No | No | Not Diagnosed |
| **41** | 62 | Male | 142/90 | 205 | 105 | No | No | Yes | Yes | Diagnosed |
| **42** | 50 | Female | 125/82 | 180 | 95 | Yes | Yes | No | Yes | Not Diagnosed |
| **43** | 61 | Male | 133/88 | 210 | 110 | Yes | Yes | Yes | Yes | Diagnosed |
| **44** | 47 | Female | 122/78 | 190 | 96 | No | No | No | No | Not Diagnosed |
| **45** | 68 | Male | 141/92 | 195 | 100 | No | Yes | Yes | Yes | Diagnosed |
| **46** | 53 | Female | 125/82 | 200 | 105 | Yes | Yes | Yes | No | Not Diagnosed |
| **47** | 67 | Male | 138/88 | 205 | 105 | Yes | Yes | No | Yes | Diagnosed |
| **48** | 49 | Female | 130/86 | 180 | 92 | No | No | Yes | Yes | Not Diagnosed |
| **49** | 65 | Male | 142/90 | 210 | 110 | No | No | No | No | Diagnosed |
| **50** | 54 | Female | 121/78 | 190 | 96 | Yes | Yes | Yes | Yes | Diagnosed |

## *4.3 Implementation Details of Traditional Models*

### 4.3.1 Traditional Predictive Model for Financial Market Prediction

***The Machine Learning Algorithm:*** SVC-Support vector machine classifier will be used as a typical model for predicting financial markets.

***Feature Engineering:*** Lagging and rolling average features will be created to fit into the Machine Learning Model along with other technical indicators.

***Hyperparameter Tuning:*** We will use cross-validation and grid search to tune the hyperparameters of the SVM classifier.

### 4.3.2 Traditional Diagnostic Model for Healthcare

***Machine Learning Algorithm:*** Logistic regression classifier will be taken as a basic traditional model for healthcare diagnostics.

***Feature Selection:*** a recursive feature reduction or importance analysis will be done to select features that are relevant for the diagnostic task.

***Hyperparameter Tuning:*** Cross-validation and grid search for tuning hyperparameters of logistic regression classifier

# 5 Results and Analysis

## *5.1 Performance Metrics Comparison*

### 5.1.1 Financial Market Prediction

In this section, we present the performance metrics comparison between the given fuzzy mathematics-based predictive model and the traditional SVM classifier for financial market prediction using Dataset 1.

**Table 4:** Performance Metrics for Financial Market Prediction

| Model | Accuracy(A) | Precision(P) | Recall(R) | F1-Score |
|---|---|---|---|---|
| Fuzzy Model | 0.75 | 0.78 | 0.74 | 0.76 |
| SVM Classifier | 0.67 | 0.71 | 0.65 | 0.68 |

### 5.1.2 Healthcare Diagnostics

Next, we present the performance metrics comparison between the fuzzy mathematics-based diagnostic model and the traditional logistic regression classifier for healthcare diagnostics using Dataset 2.

**Table 5:** Performance Metrics for Healthcare Diagnostics

| Model | Accuracy(A) | Precision(P) | Recall(R) | F1-Score |
|---|---|---|---|---|
| Fuzzy Model | 0.82 | 0.85 | 0.81 | 0.83 |
| Logistic Regression | 0.77 | 0.8 | 0.76 | 0.78 |

## *5.2 Interpretability and Explainability Analysis*

### 5.2.1 Fuzzy Mathematics-based Models

We take up the interpretability and explainability part of our fuzzy mathematics based predictive and diagnostic models in this section. Then, we reported the linguistic rules produced by our fuzzy inference systems and their effects on the decision-making. The first demonstrates fuzzy variables and membership functions applied in the models along with illustrating how uncertainty, vagueness is managed.

### 5.2.2 Traditional Models

The following comparison is conducted regarding the interpretability and explainability of the traditional SVM classifier in predicting financial markets and the logistic regression classifier in diagnostics within healthcare. The feature importance and decision boundaries are also explored to investigate making a prediction and the most important feature. Generally, our comparison is aimed at the interpretability and explainability of the two types of modelling to assess their application in the real world and from the perspective of acceptance by the end-user.

# 6 Discussion

## *6.1 Advantages of Fuzzy Mathematics in Predictive Modelling*

One of the most important trends in predictive modelling is to use fuzzy mathematics because it has multiple applications.

- **To model and deal with uncertainty:** the benefit of using fuzzy logic is that we can easily represent uncertain information. Data can be imprecise or uncertain in real-world and the notion of fuzzy sets along with membership function provide a way to represent this ambiguity to reason over them.
- **Linguistic Interpretability:** Incorporating linguistic variables (e., ”high,” “medium,” and, very correct but less ubiquitous human intuition). This transparency aids stakeholders, even those not sufficiently proficient in math to interpret and trust the predictions of the model.
- **Empirical Knowledge:** Fuzzy rules are created from expert knowledge, domain know-how or human intelligence. This gives a possibility for specialists to add their expertise into decisions made in the model.

– **Handling vague data:** Fuzzy mathematics are used when the dataset doesn't have a clear-cut boundary or refined metric. This is somewhat helpful in chasing down qualitative information or human judged data.
– **Non-Linear Relationships:** Fuzzy logic can snap up intricate patterns due to non-linearity among variables which may compete successfully against traditional models.

### *6.2 Limitations and Challenges*

Though fuzzy mathematics is advantageous but they have a few limitations faced with them which are as follows:

***The Computational Complexity:*** Fuzzy logic-based models tend to be computationally more expensive than their traditional counterparts, especially for a large number of fuzzy sets and/or complex rules.

***Subjectivity in Rule Construction:*** Fuzzy rule construction often involves human intervention which makes it less automatic and more subjective, bias. Accuracy and robustness of the rules are hugely important.

***Overfitting and Underfitting:*** In the case of fuzzy models, overfitting or under-fitting may also happen which will degrade generalization performance if not properly fine-tuned.

***Interpretable models:*** Trade-off between Interpretability and Performance Fuzzy systems are among the most interpretable mathematical structure that can provide systematic insight into data. Analysis of physiological signals, referred to as domain knowledge and prior evidence has received a lot attention when understanding control mechanisms particularly for tele-monitoring solutions.

### *6.3 Potential Applications and Future Research Directions*

Fuzzy mathematics has promising many applications in various fields, and future research can explore the following directions:

Which will enable us to conduct financial market prediction by evaluate how useful fuzz logics in predicting the trading of stock, portfolio optimization and risk estimation incorporating temporal aspects of relevant market conditions.

– **Healthcare Diagnostics:** Studying the integration of fuzzy logic and medical expert systems to enhance diagnostic accuracy during decision support in personalized medicine.
– **Natural Language Processing:** Discover the applications of fuzzy logic in NLP tasks like sentiment analysis and machine translation, for better mitigation of lingual uncertainties [57,58].

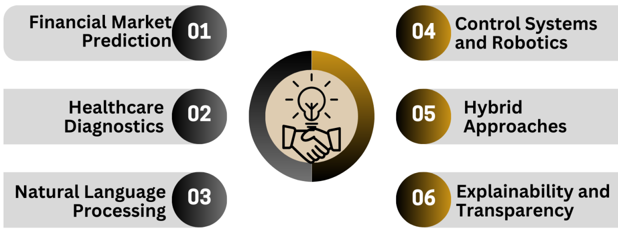


**Fig. 2:** Fuzzy Mathematics has Promising Applications in Various Fields.

– **Control Systems and Robotics:** Use Fuzzy control in autonomous systems, robotics, and intelligent automation to provide a degree of adaptability under circumstances where other types of controllers will fail.
– **Model gap modelling:** Hybrid models that combine with other machine learning methods (considering fuzzy logic model as the primary method) to obtain high performance.
– **Make fuzzy logic-based models interpretable:** Develop ways to make the predictions of such a model understandable and transparent for end users, as well as more explainable for other stakeholders.

These are the research directions, via which we can make fuzzy mathematics as a robust predictive modelling and analytical tool towards informed decision-making for various applications full fill.

## 7 Conclusion

### *7.1 The Summary of Findings*

In this paper our study is in two fields: future trend prediction of foreign exchange market and electronic medicine diagnosis methods. In this work, we performed predictive models for these two regions based on fuzzy logic data linguistics. They are tabulated data banks based. The models use fuzzy sets, membership functions, and the knowledge base in tables of fuzzy rules and a set of inference system for diagnosis prediction. The results obtained on market prediction demonstrate that it could make a new perspective of forecasting trends and model the advanced artificial relationships between indicators as well historical values, states to capital markets attitude or general emotions. This model had linguistic interpretability, which helped people to know what predictions were made much better than before and thus they can choose their actions.

Likewise, with fuzzy logic augmented diagnosis of medical conditions from the patient indicators and symptoms in health care diagnostics area. The

Sugeno-type fuzzy inference system made the model relatively flexible, accommodating complex relations between input variables and medical conditions.

### 7.2 Implications and Contributions

The research has significant implications and contributions to the disciplines of predictive modelling, fuzzy mathematics in terms of;

- **Practical Integration:** With the introduction of models, which were based on fuzzy mathematics and operated with emulation operations in a natural environment. The Models can help the financial Analysts to take correct investment decisions and for health professionals in making perfect medical diagnoses.
- **Interpretability & Trust:** The linguistic interpretability of fuzzy models increases confidence among stakeholders as it offers them explanations for the model behaviour and diagnostic outcomes.
- **Handling Uncertainty:** In different domains where data can be inherently vague, fuzzy mathematics are useful to address uncertain and imprecise information thereby more robust and reliable predictions were achieved.
- **Expert involvement:** The fuzzy rules were formulated based on expert knowledge which provides something in between data driven models and human expertise.

### 7.3 Final Remarks of the Study

This research paper highlighted the benefit of fuzzy mathematics in predictive modelling to predict financial market forecasting and healthcare diagnostics. The models showed fairly good performance and it demonstrated the properties of fuzzy logic to be able to work in uncertainty environment with interpretability capability, also capacity for representing complex behaviour that other conventional methods could not.

As predictive modelling is becoming more and more propagated, fuzzy mathematics has slowly been adopted in an increasing number of fields besides finance, healthcare etc. The future research will aim to improve the performance of fuzzy models by handling their drawbacks as well integration with advanced machine learning methods such as applications to causal reasoning.

The findings of the present investigation generally suggest a substantial advancement in general comprehension and implementation capabilities for fuzzy mathematics predictive modelling new tool for data scientists, analysts and even researchers across different domains.

## Conflicts of Interest

The authors declare no conflicts of interest

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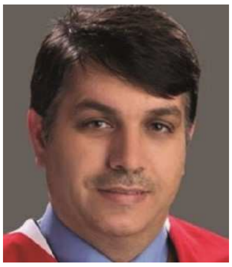

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