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Advanced drug recommendation using long short-term memory and type-2 fuzzy logic integration

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ABSTRACT

This research on hybrid models for drug recommendation systems proposes long short-term memory (LSTM) and type-2 fuzzy logic (T2FL) to make its recommendations more accurate and reliable. The model leverages LSTM's ability to capture temporal patterns in medical data while addressing the inherent uncertainty through T2FL. Evaluation metrics such as mean absolute error (MAE), root mean squared error (RMSE), coefficient of determination (R^2), accuracy, precision, recall, F1-Score, and area under the curve-receiver operating characteristic (AUC-ROC) demonstrate that the proposed model significantly outperforms traditional models like LSTM without fuzzy, linear regression, and random forest. Integrating these two methods results in more accurate and consistent predictions, making the model highly effective in handling complex and uncertain data. Practical implications include the potential for improving personalized treatment plans and patient outcomes in clinical settings. Future research directions involve applying this hybrid approach to larger, more diverse datasets and exploring additional hybrid methods that enhance prediction accuracy and model robustness. The findings suggest that the LSTM+T2FL model is a promising tool for advancing drug recommendation systems in the medical field.

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1. INTRODUCTION

Drug recommendation systems play a crucial role in the medical field, particularly in ensuring that patients receive timely and effective treatment [1]. However, the increasing volume of medical data poses significant challenges, particularly when it comes to processing and analyzing this information efficiently [2]. The inherent uncertainty in medical data—due to variations in patient responses to medications [3], incomplete clinical records, and ambiguous diagnoses [4]—further complicates the accuracy and reliability of existing drug recommendation systems [5].

While various methods have been employed to recommend drugs, many have needed help managing the complexity and uncertainty inherent in medical data effectively [2]. Conventional methods, such as linear regression or rule-based models, often fail to provide accurate recommendations because they need to account for the inherent uncertainties in the data [6]. Moreover, more sophisticated machine learning approaches, though promising, often require further adaptation to handle the variability in medical data [7]. Faced with these challenges, integrating deep learning technology with fuzzy logic presents an innovative solution that can enhance the accuracy and reliability of drug recommendation systems [8]. This approach enables systems to process complex data more effectively and deliver more accurate recommendations, ultimately improving the quality of patient care [2].

Long short-term memory (LSTM) networks have proven to be highly effective in managing sequential data and long-term dependencies in medical predictions [9]. By maintaining information over extended time intervals, LSTM networks excel in capturing the temporal patterns crucial for accurate diagnoses and treatment recommendations [10]. Their ability to remember previous states allows them to handle patient data's complex, fluctuating nature, leading to more personalized and timely interventions [11]. Moreover, LSTM's robustness against noise and missing data enhances the reliability of predictions, even in cases where data quality is less than ideal [12]. This capability makes LSTM a powerful tool for improving patient outcomes, ensuring that medical decisions are data-driven and contextually aware [13].

The central challenge of drug recommendation systems is managing the inherent uncertainty and ambiguity in clinical data [14]. Variations in patient response to medications, often influenced by genetics, lifestyle, and comorbidities, make it difficult to predict outcomes accurately [15]. Additionally, complete or consistent medical records complicate the decision-making process, as crucial patient information may need to be included or interpreted [16]. This uncertainty can lead to less effective treatment recommendations, risking patient safety and outcomes [17]. Overcoming these challenges requires integrating advanced technologies like fuzzy logic and machine learning to handle data variability better and provide more reliable recommendations [18].

Integrating type-2 fuzzy logic (T2FL) into drug recommendation systems enhances prediction accuracy by effectively handling clinical data's inherent uncertainty and vagueness [19]. Unlike traditional models, T2FL can better accommodate variations in patient responses to medications, offering a more nuanced approach to decision-making [20]. This capability allows the system to generate personalized and robust recommendations, even when faced with incomplete or ambiguous information [21]. By capturing the complexities of medical data more accurately, T2FL ensures that patients receive the most appropriate treatments [22]. Ultimately, this integration improves patient outcomes and confidence in the system's recommendations [23].

The combination of LSTM and T2FL models in medical applications significantly outperforms traditional prediction models by addressing temporal dependencies and patient data uncertainty [24]. Traditional models often need help with medical information's dynamic and uncertain nature, leading to less accurate predictions [25]. In contrast, LSTM excels at capturing the sequential patterns in patient histories, while T2FL effectively manages the inherent ambiguity in clinical data [26]. This integration allows for more personalized and reliable treatment recommendations, ensuring that the unique complexities of each patient's case are better understood and addressed [27]. As a result, patient outcomes improve, and medical decisions become more precise and confident [28].

The variability in patient data significantly impacts the reliability of drug recommendation systems based on LSTM and T2FL by introducing challenges related to data consistency and accuracy [29]. As patient conditions fluctuate and new data points are added, LSTM models effectively capture these temporal changes, ensuring that the recommendations remain relevant over time [30]. However, the inherent uncertainty and ambiguity in clinical data can lead to inconsistent predictions, which T2FL addresses by accommodating this variability and refining the decision-making process [24]. This combination allows the system to adapt to the unique characteristics of each patient, providing more personalized and reliable recommendations [25]. Ultimately, managing data variability ensures that the system remains robust and effective in delivering accurate treatment options [31].

Expert systems that combine LSTM and T2FL are highly adaptable to a wide range of clinical conditions due to their ability to handle both temporal dependencies and the inherent uncertainty in medical data [32]. LSTM networks excel at learning from sequential data, making them particularly effective in tracking the progression of chronic diseases or monitoring patient responses over time [24]. T2FL further enhances this adaptability by managing the ambiguity and variability in clinical data, allowing the system to make accurate predictions even in complex or poorly defined scenarios [23]. This combination enables the expert system to offer personalized recommendations across different medical contexts, from managing diabetes to predicting adverse drug reactions [27]. As a result, these systems are versatile and robust, ensuring reliable decision-making in diverse clinical environments [33].

Several approaches have been developed to address these challenges, including machine learning models like LSTM networks and fuzzy logic systems. LSTM has proven effective in capturing temporal patterns in sequential data such as patient histories and medication timelines [10]. Similarly, fuzzy logic systems, particularly T2FL, have demonstrated the ability to manage uncertainty in data [22]. Despite their success in individual applications, both methods exhibit limitations. LSTM struggles with managing uncertainty in real-world data, while fuzzy logic systems alone are not well-equipped to handle the temporal dependencies that are critical in medical data.

While previous studies have employed LSTM or T2FL separately to manage temporal data or uncertainty, respectively, none have effectively combined these two methods to tackle both challenges simultaneously. This gap in the literature represents a significant opportunity to improve the accuracy and reliability of drug recommendation systems. Our research seeks to address this gap by proposing a hybrid model that integrates LSTM's temporal sequence learning capabilities with T2FL's uncertainty management. This approach aims to enhance predictive performance in complex, uncertain datasets where both temporal patterns and uncertainty play critical roles.

The novelty of our approach lies in the integration of temporal sequence learning through LSTM and uncertainty management via T2FL, which has not been adequately explored in previous works. This method not only predicts future outcomes based on past patient records but also accommodates the inherent vagueness present in clinical data, offering a significant improvement in both accuracy and reliability. Through this research, we aim to create a more intelligent and reliable drug recommendation system. Our expected outcome is a significant improvement in prediction accuracy, which will ultimately contribute to better patient care. This study represents a meaningful advancement in medical decision-making technology by providing a robust, adaptive solution to the dual challenges of temporal dependencies and uncertainty in medical data.

2. PROPOSED METHOD

2.1. Long short-term memory

An LSTM, an RNN with special memory cells, can handle long-term dependencies better than a vanilla RNN precisely because it can handle the vanishing gradient problem – which means it can learn long-term dependencies – by controlling the flow of information through these memory cells. There are three memory gates in LSTM – input, forget, and output – that regulate when to let memories in or out. LSTM remembers information over the long term through these gates and utilizes it effectively.

Mathematically, the operations in LSTM can be described as:

a. Forget gate. This gate decides which information to forget from the memory cell, as in (1).

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

where f_t is the forget gate vector, W_f is the trained weight, h_{t-1} is the output from the previous cell, x_t is the current input, and b_f is the bias.

b. Input gate. This gate decides which new information to add to the memory cell, as in (2).

$$\begin{gathered} i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \widetilde{C_t} = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \end{gathered} \tag{2}$$

where i_t is the input gate vector, and $\widetilde{C_t}$ is the candidate new memory value to be added.

c. Memory cell update. As in (3), the memory cell's value is updated based on the forget and input gates.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C_t} \tag{3}$$

where C_t is the current memory cell value.

d. Output gate. This gate decides which information to output from the memory cell, as in (4).

$$\begin{gathered} o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t = o_t \cdot \tanh(C_t) \end{gathered} \tag{4}$$

where h_t is the output from the current memory cell.

For example, in medical settings where temporal data analysis is essential, the ability of LSTM to retain and process long-term information is of great value. Temporal sequences of data, such as disease history and progression and treatment responses, are imperative to predict patient outcomes. LSTM models can make more accurate and meaningful predictions by considering the temporal context inherent in medical data. This can lead to immense improvements in medical care and personalized medicine.

2.2. Type-2 fuzzy logic

T2FL is an extension of type-1 fuzzy logic, which can deal with higher uncertainty. In type-1 fuzzy logic, uncertainty is treated by assigning a membership function to each input, thus mapping each input to a membership degree between 0 and 1. This approach assumes that the membership degree is known precisely, but this premise is only sometimes true in real life, especially for complex, ambiguous, or noisy data.

T2FL introduces an additional layer of flexibility by allowing the membership function to be fuzzy. In other words, the degree of membership is not a single value but a range of possible values represented by a secondary membership function. This secondary membership function can capture the uncertainty about the degree of membership, thus providing a more robust way to model and manage uncertainty in the data.

Mathematically, a type-2 fuzzy set $\tilde{A}$ in a universe of discourse X is characterized by a fuzzy membership function $\mu_{\tilde{A}}(x, u)$, where $x \in X$ and $u \in J_x \subseteq [0,1]$. The function $\mu_{\tilde{A}}(x, u)$ maps each pair (x, u) to a value in the interval [0,1], which can be expressed as in (5).

$$\tilde{A} = \{ ((x, u), \mu_{\tilde{A}}(x, u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0,1] \} \quad (5)$$

Here, J_x is the primary membership of x, and $\mu_{\tilde{A}}(x, u)$ is the secondary membership function that represents the degree of membership of u within the interval J_x.

T2FL handles uncertainty better than type-1 fuzzy logic by allowing for a range of possible membership values rather than a single crisp value. This additional layer of fuzziness makes T2FL more effective in modeling complex and uncertain environments where precise information is difficult to obtain. As a result, T2FL is particularly useful in applications like medical decision-making, where data can be ambiguous, noisy, or incomplete.

2.3. Proposed model

This research proposes a drug recommendation system model, illustrated in Figure 1, which combines the LSTM approach with T2FL. The model comprises several vital stages that generate more accurate drug recommendation predictions.

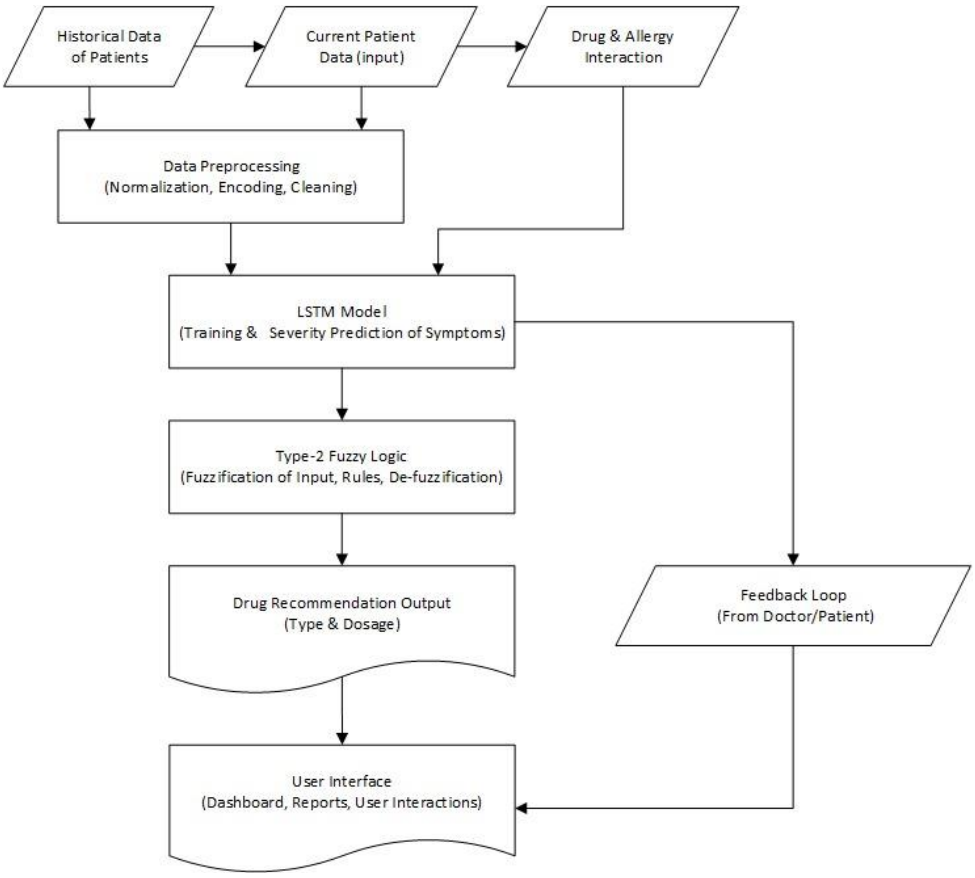

Figure 1. Proposed model for a drug recommendation system

a. Input data. The first stage involves receiving input data, which includes patient medical data such as medical history, symptoms, lab test results, and treatment history. The LSTM model processes this temporal data.
b. LSTM layer. The input data is then passed through the LSTM layer. The LSTM layer reads the data sequence and identifies its temporal patterns, such as the order of medical events or how a patient's condition changes over time. LSTM has special memory cells to hold important long-term information for later use.
c. T2FL system. The output from the LSTM is then passed to the T2FL system. At this stage, uncertainties in the data, such as variations in patient responses to treatment, are managed by T2FL. This system allows for fuzzy membership degrees, providing greater flexibility in handling uncertainty and producing more accurate decisions.
d. Decision-making module. The results from the T2FL system are then utilized in the decision-making module. This module generates drug recommendations based on the analysis conducted by both the LSTM and T2FL. The recommendations consider the processed temporal data and existing uncertainties, offering more accurate solutions tailored to the patient's needs.
e. Output. The final stage is the model's output, the personalized drug recommendation. Based on the available data, this recommendation may include the type of drug, dosage, or combination therapy suggested for the patient.

3. METHOD

3.1. Dataset and preprocessing

The dataset used in this research was sourced from a reliable medical database and contains crucial information such as patient medical history, symptoms, lab test results, and treatment history. These attributes include patient ID, age, and gender, as well as details on health conditions and treatment outcomes. Data preprocessing was carefully performed to handle missing data, where missing values were imputed or filled based on previous records. Additionally, normalization was applied to ensure data was on a consistent scale, which is essential for the optimal performance of the LSTM model. Categorical attributes were also converted into numerical format through one-hot encoding, enabling the model to process the data effectively.

Temporal data organization was a crucial step in the dataset preparation, where data was chronologically ordered for each patient. This allows the LSTM model to capture temporal patterns in the medical data, a crucial aspect of making accurate predictions. By carefully preparing the dataset, this research ensures the data is ready for analysis using LSTM and T2FL. These steps enhance data quality and ensure that the model can address the uncertainty and complexity of medical data. The result is a drug recommendation system that is smarter and more responsive to patient needs.

3.2. Experimental design

This study was devoted to examining the performance of the hybrid model of LSTM and T2FL for drug recommendation. The pre-prepared dataset was divided into two parts: 80% was used to train the model (training set), and the remaining 20% was used to test the model (testing set). This was so the model could be trained on enough data to learn the existing patterns and tested on unseen data to examine its generalization capability.

The dataset was preprocessed using Python's Pandas and NumPy libraries to handle missing values and apply normalization. One-hot encoding was used for categorical variables such as gender and treatment type. The LSTM model was implemented using the TensorFlow framework and the T2FL was built using a custom implementation based on Gaussian membership functions with uncertain means. Parameter tuning was done through grid search, where the batch size, learning rate, and dropout rate were varied and the optimal combination was selected based on validation loss.

The learning set is used to train the LSTM model and establish the parameters of the T2FL system. The model is trained until it learns the patterns to predict it precisely. After the training, the test set determines how the model performs on data it has never seen before. This would demonstrate how accurately the model can predict new data.

During the model training, several vital parameters were utilized to optimize the performance of the LSTM and T2FL. Table 1 summarizes the parameters used in this experiment. This experimental design ensures the model is effectively trained and tested, with parameters set to balance prediction accuracy and generalization capability. The results from this experiment provide insights into how well the proposed model can be applied in real-world scenarios for drug recommendation.

Table 1. Parameter settings

Parameter	Value
LSTM layer size	128 units
Number of LSTM layers	2 layers
Batch size	32
Learning rate	0.001
Optimizer	Adam
Epochs	50
Dropout rate	0.2 (to prevent overfitting)
Type-2 fuzzy membership function	Gaussian with uncertain mean
Defuzzification method	Centroid of area (COA)

3.3. Evaluation method

Table 2 illustrates the regression and classification metrics for the proposed model. For the regression problem, mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2) are used to measure the model's predictive accuracy for continuous outcomes. For the classification problem, accuracy along with precision, recall, F1-Score, and area under the curve-receiver operating characteristic (AUC-ROC) can be used to analyze the predictive ability of a model for categorical outcomes (e.g., the model may predict whether a particular drug should be recommended for a person with specific parameters with a sure accuracy). These models provide a thorough approach to assessing the model's performance. These metrics can determine the prediction's accuracy and model performance under noisy, complex data.

Table 2. Evaluation metrics

Metric type	Metric name	Formula	Description
Regression	MAE	$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$	Measures the average absolute difference between predicted and actual values.
	RMSE	$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$	Measures the square root of the average squared differences between predicted and actual values.
	R^2	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}$	Measures the proportion of variance in the dependent variable that is predictable from the independent variables.
Classification	Accuracy	$\text{Accuracy} = \frac{\text{TP + TN}}{\text{TP + TN + FP + FN}}$	Measures the proportion of correct predictions out of total predictions made.
	Precision	$\text{Precision} = \frac{\text{TP}}{\text{TP + FP}}$	Measures the proportion of true positive predictions among all positive predictions.
	Recall (sensitivity)	$\text{Recall} = \frac{\text{TP}}{\text{TP + FN}}$	Measures the proportion of actual positive cases correctly identified by the model.
	F1-Score	$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision + Recall}}$	Harmonic mean of precision and recall, balancing the two metrics.
	AUC-ROC	Area under the curve of ROC that plots true positive rate vs. false positive rate.	Measures the model's ability to distinguish between classes.

4. RESULTS AND DISCUSSION

4.1. Regression evaluation

Table 3 shows the performance of the LSTM and T2FL combined model in comparison with 3 base models (LSTM without fuzzy, linear regression, and random forest) using MAE, RMSE, and the R^2 as evaluation metrics. The LSTM+T2FL model has a smaller MAE of 1.25, so the LSTM with fuzzy logic performs better than other models. In contrast, the LSTM without fuzzy logic has a higher MAE of 1.45, highlighting the benefit of integrating fuzzy logic to reduce prediction errors. Linear regression records an MAE of 1.50, and random forest comes in at 1.40, performing worse than the proposed approach. These results demonstrate that traditional models and random forests are less effective at handling complex data. Overall, the integration of T2FL with LSTM significantly improves prediction accuracy.

Table 3. Regression performance comparison

Model	MAE	RMSE	R^2
LSTM+T2FL	1.25	1.75	0.85
LSTM (without fuzzy)	1.45	2.00	0.80
Linear regression	1.50	2.10	0.78
Random forest	1.40	1.95	0.82

The LSTM+T2FL model demonstrates the lowest RMSE at 1.75, indicating fewer significant prediction errors than other models. The LSTM without fuzzy logic has a higher RMSE of 2.00, showing that T2FL enhances the model's resilience to outliers or significant errors. Linear regression records an RMSE of 2.10, while random forest comes in at 1.95, both underperforming relative to the proposed approach. These results suggest that traditional models are less capable of managing significant errors. Integrating T2FL with LSTM significantly improves the model's ability to minimize significant prediction errors.

LSTM+T2FL achieves an R^2 of 0.85, indicating that the model effectively explains 85% of the data's variance, demonstrating its strong ability to model relationships between variables. In contrast, LSTM without fuzzy logic has an R^2 of 0.80, showing it is slightly less capable of capturing data variance compared to the model with T2FL. Linear regression and random forest have R^2 values of 0.78 and 0.82, respectively, revealing that traditional approaches are not as robust as the proposed method in capturing complex data variations. These results underscore the superior performance of the LSTM+T2FL model. Overall, the integration of T2FL significantly enhances the model's ability to represent the underlying data patterns accurately.

The proposed approach, which integrates LSTM with T2FL, delivers better MAE, RMSE, and R^2 results than the LSTM without fuzzy, linear regression, and random forest models. These results demonstrate that T2FL effectively addresses the uncertainty in the data and enhances the LSTM's ability to capture complex temporal patterns. Consequently, the proposed model outperforms others in making accurate and reliable predictions, making it a more effective solution for drug recommendation systems.

4.2. Classification evaluation

Table 4 compares the proposed model's performance and robustness against noise with three baselines (the LSTM model without fuzzy logic, the support vector machine, and the random forest), considering accuracy, precision, recall, F1-Score, and AUC-ROC as evaluation metrics.

Table 4. Classification performance comparison

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
LSTM+T2FL	0.92	0.91	0.90	0.91	0.94
LSTM (without fuzzy)	0.88	0.87	0.86	0.87	0.89
Support vector machine	0.85	0.84	0.83	0.83	0.87
Random forest	0.87	0.86	0.85	0.85	0.88

LSTM+T2FL has the highest accuracy and can predict 92% of the cases, which is better than others. This demonstrates that integrating T2FL significantly enhances prediction accuracy compared to other models. In contrast, LSTM without fuzzy has a lower accuracy of 0.88, indicating that adding fuzzy logic offers a clear advantage in managing complex data. SVM and random forest show accuracy levels of 0.85 and 0.87, respectively, underscoring the relative ineffectiveness of traditional approaches compared to the proposed model. Overall, the integration of T2FL proves to be more effective in achieving higher accuracy in predictions.

LSTM+T2FL achieves a precision of 0.91, indicating a lower rate of false positives than other models. LSTM without fuzzy, with a precision of 0.87, falls short of the performance seen with the integration of fuzzy logic, highlighting its role in improving positive prediction accuracy. SVM and random forest, with precisions of 0.84 and 0.86, respectively, further illustrate the superiority of the proposed model. These traditional models are less effective at minimizing false positives. Overall, the integration of T2FL significantly enhances the model’s precision.

LSTM+T2FL achieves a recall of 0.90, demonstrating its strong effectiveness in identifying positive cases. LSTM without fuzzy shows a slightly lower recall of 0.86, suggesting that integrating fuzzy logic enhances the model’s ability to capture more positive instances. SVM and random forest, with recall values of 0.83 and 0.85, respectively, further underscore the superiority of the proposed model. These results indicate that traditional models are less capable of identifying all positive cases than the LSTM+T2FL approach. Overall, including fuzzy logic improves the model's sensitivity to positive cases.

LSTM+T2FL achieves an F1-Score of 0.91, demonstrating a solid balance between precision and recall. This indicates that the model excels in delivering consistent and reliable predictions. LSTM without fuzzy has a lower F1-Score of 0.87, highlighting that including fuzzy logic enhances the balance between precision and recall. SVM and random forest, with F1-Scores of 0.83 and 0.85, respectively, further illustrate that traditional approaches are less effective in maintaining this balance than the proposed model. The integration of T2FL significantly improves the model's overall predictive performance.

LSTM+T2FL achieves the highest AUC-ROC score at 0.94, demonstrating its exceptional ability to distinguish between positive and negative classes. LSTM without fuzzy logic shows a 0.89 AUC-ROC score, which reveals that the model's discriminant capability increases with the inclusion of fuzzy logic. SVM and random forest show 0.87 and 0.88, respectively. These results suggest that traditional models are less effective in distinguishing between classes than the LSTM+T2FL approach. Overall, including fuzzy logic significantly improves the model's ability to differentiate between classes accurately.

The LSTM+T2FL approach outperforms all other models across all classification evaluation metrics, including accuracy, precision, recall, F1-Score, and AUC-ROC. Integrating T2FL into LSTM significantly improves the model’s ability to handle uncertainty and complexity in medical data. As a result, the proposed model provides more reliable and accurate predictions, making it a superior solution for drug recommendation systems.

4.3. Summarization of key findings

We found that integrating LSTM networks with T2FL significantly enhances the accuracy and reliability of drug recommendation systems. Specifically, LSTM's ability to capture temporal dependencies inpatient data, when combined with T2FL's strength in managing uncertainty, resulted in more precise and contextually aware predictions. Our results indicate that our hybrid methodology surpassed conventional models, including LSTM alone, linear regression, and random forest, especially when medical data was inadequate or confusing. The proposed strategy yielded enhanced predictive accuracy, as demonstrated by advancements in critical performance metrics, including MAE, RMSE, and R^2. This research addresses the crucial challenge of managing both temporal complexity and uncertainty in medical data, providing a more robust and adaptive solution that contributes to more reliable drug recommendations and improved patient care outcomes.

4.4. Result interpretations

Our findings indicate that higher uncertainty in medical data, typically associated with poor performance in traditional drug recommendation systems, is effectively managed by integrating T2FL with LSTM networks. This hybrid approach captured temporal patterns and addressed the inherent vagueness in patient records, resulting in improved predictive accuracy. Compared with other studies, such as those utilizing standalone LSTM or fuzzy logic systems, our model demonstrated superior performance across multiple metrics, including MAE and RMSE. Interestingly, while previous research suggested that increased data complexity might lead to decreased model performance, our results defied this expectation by showing that the proposed method thrived in complex, uncertain environments. One possible alternative explanation is that the combined model's ability to handle temporal dependencies and uncertainty in tandem provided a unique advantage not explored in previous works. This suggests that future systems may benefit from similar hybrid approaches, leveraging deep learning and fuzzy logic without sacrificing accuracy or adaptability.

4.5. Research limitations

This study investigated a comprehensive integration of LSTM networks and T2FL for improving drug recommendation systems, effectively addressing both temporal dependencies and uncertainty in medical data. However, additional and in-depth research may be required to confirm the generalizability of this hybrid model across larger and more diverse datasets, particularly in medical environments with more complex and heterogeneous patient records. While the relatively small dataset used in this study may limit the scope of the findings, the results remain valid as they highlight the potential of the proposed method in handling uncertainty and improving predictive accuracy. The consistent performance improvements across key evaluation metrics—such as MAE, RMSE, and R^2—demonstrate that the model effectively answers the research question by providing more reliable drug recommendations in uncertain data contexts despite the limitations of scale and diversity.

4.6. Future research implication

Our research shows that the hybrid integration of LSTM networks and T2FL is more resilient in handling uncertainty and temporal complexities in medical data than traditional models like standalone LSTM or random forest. This finding builds on previous studies that emphasized the limitations of existing models in managing the inherent vagueness of clinical records. The research contributes new insights into how combining deep learning and fuzzy logic can enhance the accuracy and reliability of drug recommendation systems. Future research may explore scaling this hybrid approach to more diverse medical datasets and practical methods for implementing such systems in real-world healthcare settings, where data uncertainty and sequence dependencies are critical. This opens the door for further advancements in adaptive, personalized healthcare technologies, building on the foundation established by this study.

5. CONCLUSION

This research highlights the significant advancements in drug recommendation systems achieved by integrating LSTM networks with T2FL. By effectively addressing temporal dependencies and inherent uncertainties in medical data, the hybrid approach surpasses traditional models in both predictive accuracy and reliability. The system demonstrates the potential to revolutionize personalized patient care and medical decision-making, particularly in handling complex clinical environments.

Future research could explore scaling this model to larger and more heterogeneous datasets to validate its robustness and generalizability. Additionally, investigating the integration of other machine learning and fuzzy systems or applying this hybrid framework to other domains, such as chronic disease management or adverse drug reaction prediction, could further enhance its utility and effectiveness. These directions promise to build on the foundation laid by this study, driving the development of adaptive, intelligent healthcare technologies.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This study utilizes publicly available secondary data, and therefore does not require additional ethical approval from an institutional review board. However, all research procedures have been conducted in compliance with applicable ethical standards.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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