Navigating Flood Prediction Complexities: Harnessing Fuzzy Expert Systems and Real-Time Sensor Integration

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***Abstract*: Fuzzy Expert Systems (FESs) stand at the forefront as a pioneering amalgamation of fuzzy logic and expert systems, constituting a robust framework primed for intricate decision-making processes. Within this context, this work presents an innovative paradigm that harnesses the profound capabilities of FESs to elevate the precision of flood prediction through the seamless integration of real-time sensor data. The domain of flood prediction takes on paramount significance in the realm of disaster management, necessitating the timely and accurate identification of potential risks. By orchestrating the nuanced cognitive processes of fuzzy logic with the specialized knowledge inherent to expert systems, the methodology introduced herein serves as a tangible demonstration of FESs' potential to fundamentally reshape the landscape of flood prediction strategies. This pioneering approach, empowered by the dynamic fusion of disparate fields, stands as a testament to the evolving nature of predictive analytics. By effectively leveraging real-time sensor data, the developed system adeptly maneuvers through the intricate dynamics of flooding events, culminating in predictions that transcend traditional forecasts. The outcomes of these predictions, actionable in nature, engender a profound sense of empowerment in the realm of proactive decision-making, thereby minimizing the potential ramifications of impending flood disasters. Within this work, a thorough examination unfolds, encompassing the foundational underpinnings, the meticulous design, and the execution of the fuzzy expert system. Furthermore, the implications of this approach are rigorously tested through its application in real-world flood scenarios, providing tangible evidence of its efficacy. This holistic exploration thus unravels the transformative potential of FESs in the context of augmenting flood prediction precision, thus forming a cornerstone of disaster management frameworks that embrace resilience and adaptability. In summation, the integration of FESs in flood prediction not only symbolizes a meeting point of computational sophistication but also epitomizes the harmonious collaboration of divergent intellectual disciplines. The promise held by this approach extends beyond its current embodiment, sparking a trajectory of continued research and advancement, catalyzing innovations that can bolster the robustness of predictive models, enhance decision-making agility, and ultimately fortify communities against the unpredictability of natural disasters.**

Keywords: Fuzzy Expert Systems, Flood prediction, Real-time sensor data, Disaster management, Fuzzy logic and Decision-making empowerment..

I. INTRODUCTION

Expert systems serve as AI tools that empower humans to make more informed decisions compared to non-experts. They act as instruments for automating decision-making processes based on existing expert knowledge. [1] developed an expert system that involved user interaction through an interface. This interface facilitated queries and data input to the knowledge base-connected inference engine. The knowledge base contained historical data related to the problem at hand. The inference engine, knowledge base, and learning module were interconnected bi directionally. The inference engine transferred historical data to the learning module for updating the knowledge base, ensuring a continuous learning process within the system.

[2] presented the development of an expert system specialized in water resource management. They introduced an intelligent interface called HYDRO, which assists in selecting appropriate numerical values for input parameters in a simulation program called HSPF. [3] focused on the creation of an expert system aimed at river flood defense and control. They discussed the essential simulation models and human input required to develop such a system. A conceptual framework for the expert system was provided, emphasizing its role in supporting flood control operations. Drawing from a collection of mathematical models, [4] comprehensively reviewed expert systems in water resource management up to the year 1983. This review was presented during an ASCE conference, providing insights into the state of expert systems at that time. [5], wherein Turbon recognized expert systems (ES) as a means to transfer human domain knowledge to a computer. A crucial aspect of a competent ES lies in its knowledge-base, which relies on a knowledge representation scheme capable of effectively addressing flood risk-related matters. To achieve an expert system for flood risk assessment, [6] recommended employing a BRB inference methodology in combination with RIMER during the system's design process.

II. MATERIAL AND METHODS

The heading, as depicted in Figure 1, outlines the approach employed for building the backend of our IoT-based FES. In the IoET-based FES, the data collection subsystem comprises sensor data and historical data, which serves as the foundation for generating knowledge [7]. This data compilation incorporates both dynamic sensor data and static historical data. The Communication Subsystem gathers data through telemetry and stores it in a database. The sensor-collected data is utilized for dynamic data integration, while historical data is employed for static data integration. Subsequently, these database-stored data are exclusively utilized for knowledge generation within the expert systems. The [11-12] FES utilizes fuzzy logic to assess the probability of events occurring, leveraging its advantage of incorporating expert knowledge into the system. The main goal is to predict flood risk effectively[13-14] by analysing water level and precipitation data.

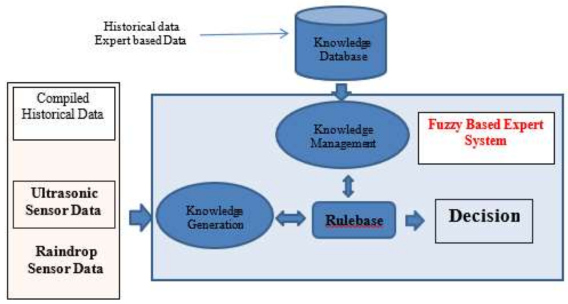

Fig. 1. IoT based FES framework for flood risk

Data integration occurs after the collection of raw data [8], which is then converted into meaningful data suitable for storage in a database. Once this data is transformed and made meaningful, it becomes accessible for utilization by the Expert System. The knowledge base uses this information to supply data to the inference engine [15], which generates outcomes based on different conditions.

III. Research Methodology

Fuzzy logic employs fuzzy sets and fuzzy operators as its subjects and verbs, respectively. In the context of flood warning, the role of fuzzy logic is to establish a mapping between water level and the presence of precipitation. This mapping is exemplified in Fig.1. using if-then statements. Before developing a rule-based system to interpret these statements, it is essential to define all terms and adjectives involved. The sequence of rules does not impact the process. To determine if the water level poses a hazard, we need to specify the range of the average water level. "To ascertain the water's risk level, it is necessary to establish the range of average water levels. The fuzzy inference procedure is illustrated in Fig.1. Before developing an expert system tailored to a particular area, it is crucial to assess the historical occurrence of flooding events. The risk assessment process is directly influenced by the existing precipitation and water level, which are presumed to be contributing factors."

Therefore, while creating an unclear system, these two factors and historical data are used to establish a threshold value. Fig. 2. Typically, a FES operates on a limited number of principles and operations, which are outlined as follows Table I:

Few operations also used in the proposed FES are:
(i) AND Operation (ii) OR operations
(iii) Not on AND Operation

TABLE I. LOGICS TABULATION

W_{LN}	R_{LN}	W_{LN}	^	R_{LN}	W_{LN}	R_{LN}	W_{LN} V R_{LN}	W_{LN}^	R_{LN}	!W_{LN}^R_{LN}
0	0	0			0	0	0	0		1
0	1	0			0	1	1	1		0
1	0	0			1	0	1			0
1	1	1			1	1	1			0

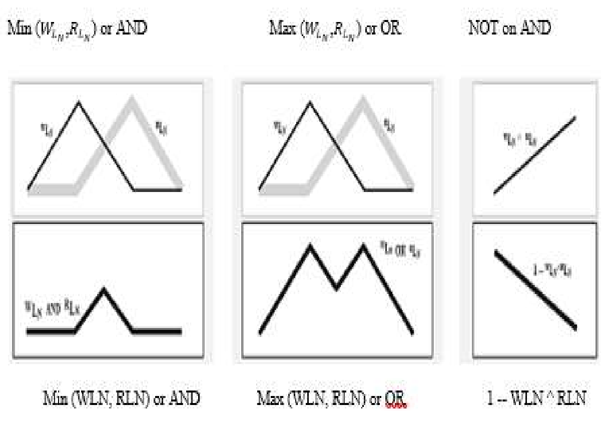

Fig 2. Graphical representation of logics

A. *Designed If-Then rules*

If-then rule statements play a crucial role in formulating the conditional statements utilized in fuzzy logic, namely, if-then statements.

There is no risk when the water level is below average or when rainfall is below normal. Likewise, if both water levels and precipitation are below average, there is no risk.

However, a risk exists if the water level is above normal and rainfall levels are normal, or if water levels are normal and rainfall levels are above normal.

Moreover, a high risk is present if both the water level and rainfall level are above normal.

All these if-then statements follow the format "if x is A, then y is B." In this context, "x is A" represents the "antecedent," and "y is B" represents the "consequent." The antecedent includes terms like "below normal," "normal," and "dangerous," while the consequent incorporates terms like "No risk and No warning," "Risk and Warning," and "high risk and warning." These terms are mapped to numbers between 0 and 1, indicating their relevance and contributing to better interpretation, with 0 representing absence and 1 representing certainty on a specific condition's scale from 0 to 1.

B. Antecedent and consequent generation mechnaism

In order to assess the flood risk, the researcher relied on historical data spanning the past century. They analyzed the average daily precipitation over this period and identified precipitation levels surpassing this average as hazardous. Through this historical analysis, the researcher also identified the highest recorded precipitation level and corresponding flood in the region. Subsequently, the researcher identified precipitation and hazard levels as key factors in determining the risk of flooding.

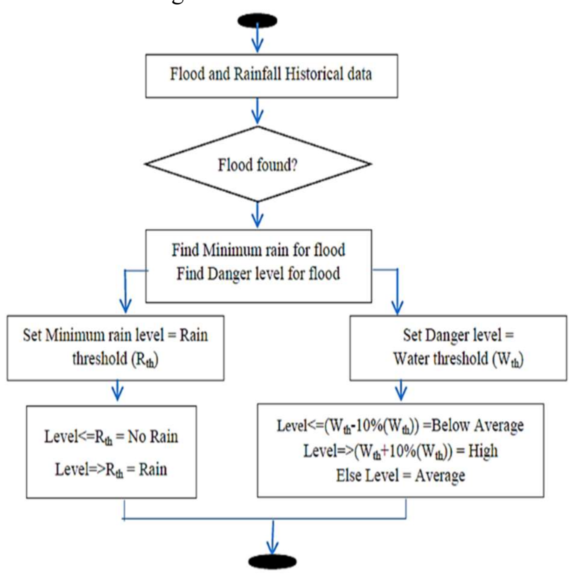

Fig.3 Antecedent and consequent generation mechanism.

In the interpretation, all the antecedents in all the statements are evaluated first before applying a fuzzy operator on it and then the result of those statements is used.

C. Rules Development

Fig. 4. illustrates the methodology employed in an IoT-based FES for evaluating the probability of a deluge. The system utilizes risk categories that are based on water level and precipitation level to determine the likelihood of a flood. Please refer to Fig. 3. for a visual representation of the process.

D. Fuzzy Interface process

The Fuzzy inference process in our system consists of five distinct steps:

1. Fuzzification of the input variables,
2. Application of the fuzzy operator (AND or OR) in the antecedent,
3. Implication from the antecedent to the consequent,
4. Aggregation of the consequents across the rules, and
5. Defuzzification using the specified Membership Functions, Logical Operations, and If-Then Rules.

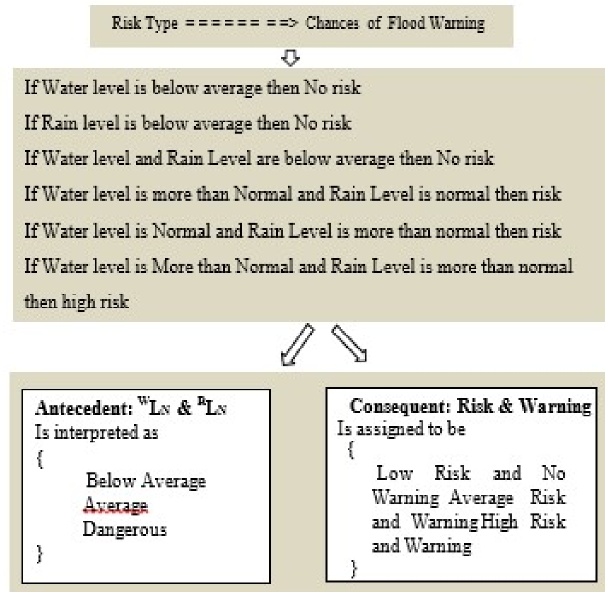

Fig. 4. Flow chart for risk finding

IV. IDENTIFICATION OF WEAK PORT

Prior to the development of our fuzzy-based system, other expert systems like those by [9,10] were studied. The researcher found systems similar to ours in certain aspects. Some well-known systems with significant popularity include CAFFG, SIATA, and ELDEWAS. For a detailed comparison between these existing systems and our proposed ES, please refer to Table II (a) and (b).

TABLE II (A). COMPARISON IN THE COMMUNICATION LINK USED

Protocol	CAFFG	SIATA	ELDEWAS	IoT based FES
Telemetry	Yes	No	Yes	Yes
GPRS	No	Yes	No	No

TABLE II (B). Comparison of IoT based FES with others

Sensor / Data Collection Method	CAF FG	SIAT A	ELDE WAS	IoT based FES
Precipitation sensor	Yes	Yes	Yes	No
Water level sensor	No	Yes	No	Yes
Moisture sensor	No	Yes	No	No
Rainfall Sensor	No	No	No	Yes
Temperature sensor	Yes	Yes	Yes	No
Wind sensor	No	Yes	Yes	No
Historical rainfall data	No	No	No	Yes
Historical flood data	No	No	No	Yes
Other secondary data	No	No	No	Yes

The assessment of flood risk involves establishing a hypothesis based on the correlation between water level and precipitation. In this context, there are three variables, with two being independent variables and one serving as the dependent variable.

Hypothesis

Hypothesis concerns relationships between input variables and the output variable as:

• Null Hypothesis (H0): There is no significant correlation between the water level, the presence of precipitation, and the risk of flooding.

• Alternative Hypothesis (Ha): There is a significant correlation between the water level, the presence of precipitation, and the risk of flooding.

Validation

Regression analysis serves as a valuable technique for investigating the relationship between different types of variables, especially in systems with multiple input and output variables. The Table III in order to test the hypothesis, (1) multiple linear regressions were conducted, involving two independent variables as instances for the analysis.

$$y = b0 + b1x1 + b2x2 \tag{1}$$

TABLE III. DATA CALCULATION FOR MLR

Risk (Y)	Water level (x1)	Rainfall (x2)	(X1)2	(X2)2	X1Y	X2Y	X1X2
0	0	0	0	0	0	0	0
0	0	1	0	1	0	0	0
0	0.5	0	0.25	0	0	0	0
0	1	0	1	0	0	0	0
0.5	.5	1	0.25	1	0.25	0.5	0.5
1	1	1	1	1	1	1	1
$\sum Y =$ **1.5**	$\sum x_1 =3$	$\sum x_2 =3$	$\sum X^2 = 1$ 2.5	$\sum X^2$ 2 = 3	$\sum X_1Y = 1.25$	$\sum X_1Y = 1.5$	$\sum X_1X_2 =1.5$

CONCLUSION

In conclusion, the integration of Fuzzy Expert Systems (FESs) within flood prediction frameworks presents a significant advancement in disaster management strategies. This work showcased the potential of FESs to elevate the accuracy and timeliness of flood predictions by harnessing the combined strength of fuzzy logic and expert systems. The developed methodology effectively translated real-time sensor data into actionable insights, enabling decision-makers to proactively address potential flood risks. The results of applying the proposed FES-based approach to real-world flood scenarios underscore its effectiveness. The system's ability to navigate complex and uncertain data, alongside its adaptability to evolving conditions, offers a robust foundation for enhanced flood prediction. By incorporating domain expertise and intricate reasoning, the FES demonstrated its potential to outperform traditional prediction models, ultimately leading to more informed and effective decision-making in disaster-prone areas. The success of this endeavor opens avenues for further research and development in the realm of FESs. The work's findings emphasize the importance of continuous data integration, system refinement, and collaboration with experts to continually enhance prediction accuracy. As disasters such as floods become increasingly frequent and severe, the utilization of FESs holds promise for building resilient communities and safeguarding lives and infrastructure through advanced, data-driven decision support systems.

REFERENCES

[1] Eldho, T.I.; Zope, P.E.; Kulkarni, A.T. Urban flood management in coastal regions using numerical simulation and geographic information system. In Integrating Disaster Science and Management: Global Case Studies in Mitigation and Recovery; Elsevier: Amsterdam, The Netherlands, 2018; pp. 205–219.

[2] Zhang, C.; Fan, C.; Yao, W.; Hu, X.; Mostafavi, A. Social media for intelligent public information and warning in disasters: An interdisciplinary review. Int. J. Inf. Manag. 2019, 49, 190–207.

[3] Bachmann, D.J.; Jamison, N.K.; Martin, A.; Delgado, J.; Kman, N.E. Emergency Preparedness and Disaster Response: There's An App for That. Prehosp. Disaster Med. 2015, 30, 486–490.

[4] Castanhari, R.E.S.; Dos Santos Rocha, R.; De Andrade, S.C.; De Albuquerque, J.P. A software architecture to integrate sensor data and volunteered: Geographic information for flood risk management. In Proceedings of the International ISCRAM Conference, Rio de Janeiro, Brasil, 22–25 May 2016.

[5] Webster, J.; Watson, R.T. Analyzing the past to prepare for the future: Writing a literature review. MIS Q. 2002, 26, 13–23.

[6] Adelekan, I.O. Flood risk management in the coastal city of Lagos, Nigeria. J. Flood Risk Manag. 2016, 9, 255–264.

[7] Preethi, P., Asokan, R., Thillaiarasu, N., & Saravanan, T. (2021). An effective digit recognition model using enhanced convolutional neural network based chaotic grey wolf optimization. Journal of Intelligent & Fuzzy Systems, 41(2), 3727-3737.

[8] Bai, D. P., & Preethi, P. (2016). Security enhancement of health information exchange based on cloud computing system. International Journal of Scientific Engineering and Research, 4(10), 79-82.

[9] Preethi, P., & Asokan, R. (2020, December). Neural network oriented roni prediction for embedding process with hex code encryption in dicom images. In Proceedings of the 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), Greater Noida, India (pp. 18-19).

[10] Kulurkar, P., kumar Dixit, C., Bharathi, V. C., Monikavishnuvarthini, A., Dhakne, A., & Preethi, P. (2023). AI based elderly fall prediction system using wearable sensors: A smart home-care technology with IOT. Measurement: Sensors, 25, 100614.

[11] F. Arrofiqi, T. Watanabe and A. Arifin, "Design of Parameter Estimation Method of Fuzzy FES Controller: Computer Simulation Test in Wrist Joint Control," 2022 IEEE 4th Global Conference on Life Sciences and Technologies (LifeTech), Osaka, Japan, 2022, pp. 116-120, doi: 10.1109/LifeTech53646.2022.9754880.

[12] Noorsal, E.; Arof, S.; Yahaya, S.Z.; Hussain, Z.; Kho, D.; Mohd Ali, Y. Design of an FPGA-Based Fuzzy Feedback Controller for Closed-Loop FES in Knee Joint Model. Micromachines 2021, 12, 968. https://doi.org/10.3390/mi12080968.

[13] Y. Suppakhun, "Flood surveillance and alert system an advance the IoT," *2019 IEEE Asia Pacific Conference on Circuits and Systems (APCCAS)*, Bangkok, Thailand, 2019, pp. 325-328, doi: 10.1109/APCCAS47518.2019.8953179.

[14] J. M. A. Opella and A. A. Hernandez, "Developing a Flood Risk Assessment Using Support Vector Machine and Convolutional Neural Network: A Conceptual Framework," 2019 IEEE 15th International Colloquium on Signal Processing & Its Applications (CSPA), Penang, Malaysia, 2019, pp. 260-265, doi: 10.1109/CSPA.2019.8695980.

[15] Reis, T.; Funke, T.; Bruchhaus, S.; Freund, F.; Bornschlegl, M.X.; Hemmje, M.L. Supporting Meteorologists in Data Analysis through Knowledge-Based Recommendations. Big Data Cogn. Comput. 2022, 6, 103. https://doi.org/10.3390/bdcc6040103