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An adaptive neuro-fuzzy inference system for software development risk assessment in uncertain environments

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ABSTRACT

Relevance. The paper addresses the problem of achieving effective risk management in software development projects under conditions of severe uncertainty, ambiguity, and high volatility. Traditional risk management approaches, which rely on rigid quantitative techniques or precise mathematical formulations, often prove ineffective due to limited initial information and the highly subjective nature of expert judgments, highlighting the need for flexible, dynamic, and adaptive decision-making models. **Aim of the article.** The purpose of the study is to introduce, design, and validate an innovative decision-making framework based on an Adaptive Neuro-Fuzzy Inference System to significantly improve both the accuracy and adaptability of risk assessment and classification in software engineering. **Tasks.** The research focuses on formalizing software project risk parameters under incomplete data, integrating the data-driven learning capabilities of neural networks with fuzzy logic mechanisms into a unified inference architecture, conducting an empirical evaluation using real-world project datasets, and performing a comparative analysis against conventional risk management techniques. **Methods.** The proposed framework is developed using the Adaptive Neuro-Fuzzy Inference System architecture, which combines the adaptive learning strengths of neural networks with the uncertainty-handling capabilities of fuzzy logic. The methodology is implemented and validated through empirical simulation and comparative testing against classical analytical techniques using real-world project data. **Scientific novelty.** The study lies in the design and application of a hybrid neuro-fuzzy model that comprehensively addresses uncertainty, automatically accounts for risk interdependencies, and dynamically adapts to variations in changing project environments, offering a significantly higher precision framework compared to traditional standalone fuzzy or statistical solutions. **Practical significance.** The proposed Adaptive Neuro-Fuzzy Inference System -based framework is highly applicable within decision-support systems, software project monitoring tools, and automated risk-management modules to provide continuous, resilient, and automated risk classification under dynamically evolving or incomplete data conditions. **Results.** Empirical evaluation using real-world project datasets demonstrates that the proposed ANFIS model substantially outperforms conventional fuzzy inference systems and analytic hierarchy process (AHP) techniques, attaining a high risk-classification accuracy of ninety-four point seven percent while exhibiting excellent stability across diverse input scenarios. **Conclusions.** The developed neuro-fuzzy framework is established as a highly precise, flexible, and promising solution for advancing risk management practices in software engineering, successfully overcoming the limitations of traditional methodologies regarding precision, adaptability, and flexibility in volatile environments.

Keywords: Risk management; uncertainty; fuzzy logic; decision-making model; neuro-fuzzy model; IT technologies

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INTRODUCTION

In the context of ongoing digital transformation and rapid advances in information technology, risk management in software development projects has become increasingly important.

High levels of uncertainty, complex requirements, rapidly changing project environments, and human-related factors create numerous risks that can substantially affect software quality, project budgets, and delivery schedules. In this study, software development risk management is understood as a systematic process of identifying, assessing, prioritizing, monitoring, and responding to factors that may adversely affect the achievement of software project objectives. These risks may arise from changing requirements, schedule delays, budget constraints, insufficient resources, technical complexity, software defects, team conflicts, and interdependencies among project activities. Their

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consequences may include increased development costs and duration, reduced software quality, decreased team productivity, and failure to achieve the planned project outcomes. The criticality of each risk is determined by both its likelihood of occurrence and the severity of its potential consequences. Therefore, risks characterized by a high likelihood and significant impact require priority assessment and timely managerial intervention. Accordingly, there is a pressing need for advanced decision-making models and methodologies capable of adequately addressing uncertainty and incorporating multiple evaluation criteria.

Traditional risk assessment approaches may struggle to aggregate heterogeneous and imprecise expert information without increasing information loss. Under such conditions, intuitionistic fuzzy aggregation operators can improve information fusion quality by reducing uncertainty and preserving decision-relevant information in the multi-criteria assessment of software development risks [2]. Consequently, fuzzy logic, neural networks, and their hybrid variants are gaining prominence, enabling the integration of quantitative and qualitative indicators into unified risk analysis models [14]. Current studies also focus on identifying and prioritizing technical risks in machine-learning-based software projects. A structured model developed using multinational expert data and a modified Delphi-AHP method enables the significance of technical risk factors to be determined and supports risk-oriented decision-making in software development [5]. Nevertheless, models based on predefined factor hierarchies and expert-derived weights may have limited ability to adapt to dynamic changes and capture nonlinear interdependencies among heterogeneous risk factors. Neglecting these aspects may lead to inaccuracies in risk evaluation, inefficient resource allocation, and project delays. Therefore, developing integrated adaptive models capable of comprehensively addressing these dimensions remains a critical and timely research objective.

In this context, the automation of risk management processes has become particularly relevant, as it reduces dependence on manual data processing and enables timely responses to project changes. Machine learning methods are increasingly employed to identify and predict risks at the early stages of software development. A study of global software development projects identified 18 significant risk factors related to requirements, project management, technical conditions, and cultural differences. Logistic regression, decision trees, random forests, support vector machines, k-nearest neighbors, and Naive Bayes were compared as risk prediction methods, with logistic regression and random forest demonstrating the highest classification accuracy [10]. Although these findings confirm the potential of data-driven risk prediction, conventional machine learning classifiers generally rely on structured numerical or categorical data and may be insufficient for representing ambiguous assessments and complex nonlinear relationships among project parameters. Optimized neuro-fuzzy networks can help overcome these limitations by combining learning capabilities with fuzzy inference, modeling nonlinear relationships, and adapting their internal parameters using historical data, thereby improving the accuracy of software development effort estimation [8]. Integrating such models into risk management processes provides a quantitative basis for identifying potential cost and schedule deviations, reduces reliance on manual calculations, and improves the timeliness and consistency of management decisions in dynamically changing software projects.

The scientific contribution of this study lies in the design and application of a neuro-fuzzy model based on the Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture, which facilitates accurate and efficient risk assessment and classification under incomplete and imprecise data conditions. The proposed model accounts for risk interdependencies and adapts to variations in project environments and parameters. This approach significantly diverges from traditional solutions by offering high adaptability and comprehensive treatment of uncertainty, as validated through experimental evaluation and comparative analyses against classical risk management techniques. The findings demonstrate that the proposed model substantially improves risk classification accuracy, accelerates decision-making, and enhances overall risk management effectiveness in software development processes. Future research directions include extending this approach by incorporating behavioral team factors and integrating it with other contemporary decision-support methodologies.

RELATED WORKS

Modern research in risk management for software development (SD) is characterized by a variety of approaches and methods aimed at addressing uncertainty and incomplete information factors. A significant portion of contemporary studies relies on fuzzy logic, neural networks, and their hybrid models.

For example, Olusanya et al. [18] proposed a neuro-fuzzy risk assessment model that effectively classifies security risks at different stages of the SD lifecycle. This model integrates the advantages of neural networks and fuzzy logic, allowing better incorporation of subjective expert evaluations and quantitative data, thus significantly enhancing the accuracy of risk prediction and improving management decision quality.

Mashaleh et al. [16] developed a model employing fuzzy logic combined with particle

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swarm optimization (PSO) for risk evaluation in IoT environments. This approach effectively addresses dynamic and unpredictable changes within IoT networks, providing high accuracy and decision-making responsiveness under conditions of significant uncertainty and complexity.

Medvedev et al. [17] applied fuzzy logic to model risks within logistic supply chains, demonstrating effectiveness in resolving multifactorial problems where classical forecasting methods often lack flexibility. This approach holds promise for adaptation to risk management tasks within software development contexts.

Gao and Zhou [9] employed fuzzy DEMATEL to analyze causal relationships between risks in manufacturing processes. Their method identifies key risks and assesses their mutual influences, particularly significant for complex systems, including SD.

Dutta and Konwar [6] suggested using quintic fuzzy sets for multi-criteria decision-making. Their method provides greater flexibility in uncertainty modeling compared to traditional fuzzy set forms (such as intuitionistic and Pythagorean fuzzy sets), thus achieving higher accuracy in risk assessment under complex and ambiguous conditions.

Mahdiraji et al. [15] developed a multilevel spherical fuzzy model applied for assessing transport system resilience. This approach can be adapted to analyze vulnerabilities within SD, effectively integrating expert evaluations of varying reliability and deeply examining individual factor impacts.

Bhat et al. [3] introduced a group-based multi-criteria decision algorithm based on q-rung orthopair fuzzy sets. This algorithm is notable for high accuracy and consistency in expert evaluations, allowing better consideration of opinion diversity and reducing the subjectivity influence in decision-making processes.

Zhao et al. [23] and Hašková et al. [11] studied comprehensive fuzzy decision support systems, effectively combining positive and negative evaluation aspects, thus ensuring high adaptability and accuracy even in cases involving substantial incomplete or imprecise data.

Dewi and Dharmawan [4] proposed a model accounting for risks during workforce planning stages in SD projects, significantly enhancing forecast accuracy by integrating historical data with fuzzy expert evaluations.

Horcas et al. [12] integrated the concept of belief uncertainty into SD release planning processes, substantially reducing deviations from planned schedules and enabling more effective management of risks related to unforeseen user requirement changes.

Additionally, recent studies highlight the importance of user-oriented approaches and behavioral factors in risk assessment and decision-making. Ziemba et al. [25] proposed a fuzzy multi-criteria group decision-making method for evaluating software systems that support remote education. Their findings demonstrated the effectiveness of fuzzy models in representing subjective user preferences and assessments, thereby improving decision-making under complex and uncertain conditions. Similarly, Espadinha-Cruz and Reboredo [7] developed a fuzzy system for assessing additive manufacturing maturity, demonstrating the ability of fuzzy logic to integrate qualitative and quantitative indicators across different application domains. In the context of software engineering, Aregbesola et al. developed a fuzzy logic model for risk assessment and informed decision-making during the software design phase. The model considers evolving architectural requirements, technical feasibility concerns, and stakeholder misalignment, while expert-defined fuzzy rules enable uncertain and imprecise information to be represented [24]. These studies demonstrate the broad applicability of fuzzy methodologies and confirm their relevance to software risk management. However, conventional fuzzy models depend substantially on predefined membership functions and expert-formulated rules, which may require manual adjustment as project conditions evolve. This limitation substantiates the application of ANFIS, in which neural learning mechanisms enable the parameters of the fuzzy inference system to be automatically adapted using accumulated project data.

Alatawi et al. proposed a data-driven artificial neural network approach for assessing risks in software projects using historical data on project complexity, financial factors, performance indicators, schedule adherence, and user-related characteristics. The developed model enables both overall project risk and individual risk factors to be predicted, demonstrating the ability of neural networks to identify complex nonlinear relationships among heterogeneous project parameters [27]. The reported results confirm the potential of data-driven intelligent models to support proactive risk mitigation and informed managerial decision-making. However, conventional artificial neural networks offer limited interpretability and do not explicitly represent uncertain or imprecise expert assessments. These limitations substantiate the application of adaptive neuro-fuzzy approaches that combine the learning capabilities of neural networks with the transparent representation and processing of uncertainty provided by fuzzy inference systems.

Despite significant advances in this field, the demand for comprehensive solutions simultaneously addressing risk dynamics, their interdependence, and human factors remains highly relevant. These challenges are specifically targeted by the neuro-fuzzy model based on ANFIS, proposed in this study.

RESEARCH AIM AND OBJECTIVES

The primary aim of this research is to design, implement, and validate an intelligent, software-implemented risk management framework based on the Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture to enhance the precision, flexibility, and automation of risk classification in software development projects under conditions of severe uncertainty, incomplete data, and environmental volatility. This framework addresses the critical limitations of conventional methodologies – such as standalone fuzzy logic systems and the Analytic Hierarchy Process (AHP) – by establishing a dynamic methodology that successfully integrates subjective expert judgments with automated, data-driven machine learning capabilities. By formulating a unified assessment mechanism that bridges the gap between qualitative indicators and quantitative project states, this study aims to provide project managers and stakeholders with a resilient decision-support tool suitable for continuous monitoring within the software development lifecycle (SDLC).

The effectiveness of software development risk assessment methods can be evaluated using a set of quantitative indicators, including risk-classification accuracy, adaptability to changes in input parameters, correct identification of critical risks, stability when data are incomplete, training time, and decision-making time. These indicators allow methods to be compared not only in terms of classification accuracy but also with regard to their practical applicability under dynamic and uncertain project conditions. In the present study, these criteria provide a unified basis for comparing the proposed ANFIS model with conventional fuzzy inference systems, AHP, and machine learning approaches. Such a comprehensive evaluation makes it possible to consider predictive performance, robustness, adaptability, and computational efficiency when assessing the practical effectiveness of software development risk assessment methods.

A recent study by Liakh et al. proposed an integrated system of methods for automating the evaluation of risk management effectiveness in software quality assurance systems. The approach combines risk exposure assessment with dynamic software quality indicators, including defect density, test coverage, mean time to failure, and security incident rate, as well as economic indicators related to risk mitigation activities. An integrated risk management effectiveness index was introduced to provide a quantitative basis for automated evaluation of risk management performance. This study demonstrates the importance of combining multiple quantitative indicators when evaluating software risk management effectiveness. However, unlike the integrated effectiveness assessment considered in that study, the present research focuses on adaptive classification of individual software development risks under uncertain and incomplete input conditions using the ANFIS architecture [26].

To achieve this primary aim, the study addresses several sequential research objectives. First, a formalized software risk framework is established by integrating five critical project parameters: requirement change frequency, defect density per unit of code, task execution delay frequency, budget overrun ratio, and team conflict levels. Second, a five-layer Sugeno-type ANFIS architecture utilizing smooth Gaussian membership functions is developed and computationally implemented within the MATLAB R2022b environment using a hybrid optimization algorithm. Third, an extensive empirical evaluation and hyperparameter fine-tuning via grid search and 5-fold cross-validation are conducted using a structured software project risk dataset to determine the optimal configuration of the proposed model. Finally, a rigorous sensitivity analysis using the one-factor-at-a-time (OFAT) method is executed to confirm the model's structural resilience and evaluate its operational stability within a ±10% input variability threshold, thereby outlining the boundaries for effective practical deployment in dynamic IT environments.

RESEARCH METHODOLOGY

To verify the effectiveness of the proposed ANFIS-based approach and evaluate its capability to accurately and promptly identify risks in software development under conditions of uncertainty, an experimental study was conducted. Within the framework of this experiment, a specialized dataset was constructed to ensure the adequacy and comprehensiveness of the methodology's evaluation. The decision-making model was developed using the MATLAB R2022b environment, specifically leveraging the built-in functionalities of the Fuzzy Logic Toolbox and the Neural Network Toolbox for ANFIS construction, training, and evaluation. This integrated development environment provided efficient tools for designing membership functions, structuring rule bases, and visualizing performance metrics. To accommodate the high computational demands of optimizing the machine learning algorithms during neuro-fuzzy model training, the experimental

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simulation was executed on a hardware configuration comprising an Intel Core i7–11700F processor at 2.50 GHz, 32 GB of DDR4 RAM at 3200 MHz, a 1 TB NVMe SSD for rapid data access, and an NVIDIA RTX 3060 GPU with 12 GB of VRAM.

The specialized dataset compiled for this study was structured to represent the main risk characteristics of software development projects under conditions of uncertainty. The dataset comprises records characterized by five input variables: requirement change frequency, defect density per unit of code, task delay frequency, budget overrun ratio, and team conflict index. These variables represent five complementary dimensions of software development risk, including requirements, software quality, schedule performance, financial deviations, and team-related factors. Requirement change frequency characterizes the intensity of changes in project requirements; defect density represents the number of identified defects per unit of source code; task delay frequency reflects the occurrence of delays in planned development activities; budget overrun ratio characterizes the relative deviation of actual expenditure from the planned budget; and team conflict index represents the level of interpersonal and coordination problems within the project team. The target variable represents the overall project risk level and is categorized into three classes: low, medium, and high. Thus, the five input variables constitute the primary risk characteristics used by the model, while the overall project risk level serves as the target variable for classification.

The dataset used for the experimental study was prepared as a structured numerical dataset for software development risk classification. Each record contains five primary input indicators and one target variable representing the overall project risk class. The primary indicators are requirement change frequency, defect density per unit of code, task delay frequency, budget overrun ratio, and team conflict index, while the target variable is represented by the low, medium, and high risk classes. Before model training, the input indicators were normalized to the [0,1] range using min-max normalization to ensure comparability of variables measured on different scales. The resulting records were used for training, validation, and testing of the ANFIS model according to the dataset partitioning procedure described below.

The adaptive nature of the proposed ANFIS model is manifested in its ability to adjust the parameters of the Gaussian membership functions and the consequent parameters of the fuzzy rules using project data. Unlike a conventional fuzzy inference system with predefined membership functions and rules, ANFIS combines fuzzy reasoning with data-driven parameter optimization, allowing the model to adapt the relationship between project risk indicators and the resulting risk level when project conditions change. Such adaptability is important because software development risks are dynamic and may vary with changes in requirements, defect rates, task delays, budget deviations, and team-related factors.

Formally, the software development risk assessment problem is defined as a multiclass classification task. Let the input vector be $(X = (x_1, x_2, x_3, x_4, x_5))$, where (x_1) is requirement change frequency, (x_2) is defect density, (x_3) is task delay frequency, (x_4) is the budget overrun ratio, and (x_5) is the team conflict index. The target variable (Y) belongs to three classes, $(Y \in L, M, H)$, corresponding to low (L), medium (M), and high risk (H). The objective is to construct an adaptive mapping $(F_{ANFIS}(X;\theta) \to Y)$, where (θ) represents the adjustable parameters of the membership and consequent functions, while minimizing the classification error on the available project data. The model is therefore required to provide accurate classification of the current risk state and maintain stable performance when the input indicators vary within the operating range considered in the study.

Before model training, all input variables were normalized to the [0,1] range using min-max normalization to ensure a common scale for the heterogeneous risk indicators. The resulting dataset provides the input-output structure required for training, validation, and testing of the proposed ANFIS model. The dataset was randomly shuffled and partitioned into training (70 %), validation (15 %), and testing (15%) subsets. This partitioning was applied to reduce potential ordering effects and provide separate data subsets for model learning, parameter selection, and independent performance evaluation.

The implemented ANFIS architecture consists of five functional layers: fuzzification, rule antecedent, normalization, defuzzification, and the output layer, which collectively execute operations such as computing membership degrees, applying Sugeno-type fuzzy inference rules, and generating crisp outputs. The Gaussian membership function was selected due to its smoothness and flexibility in capturing continuous input variations. Based on historical data analysis, expert consultations, and clustering techniques, a knowledge base containing 20 fuzzy rules was empirically defined.

For clarity, the dimensional structure, functional role, and information flow between the ANFIS layers are summarized in Table 1.

Table 1. **Dimensional and functional characteristics of the layers of the proposed ANFIS architecture**

ANFIS layer	Input dimension	Main operation	Output dimension	Connection
Input layer	5 × 1	Project risk indicators	5 × 1	Connected to fuzzification layer
Layer 1 – Fuzzification	5 × 1	Gaussian membership functions	Membership degrees	Each input is transformed into fuzzy membership values
Layer 2 – Rule antecedent	Membership degrees	Evaluation of 20 fuzzy rules	20 × 1	Rule firing strengths are passed to normalization
Layer 3 – Normalization	20 × 1	Normalization of rule firing strengths	20 × 1	Normalized strengths are passed to consequent layer
Layer 4 – Defuzzification	20 × 1	Sugeno-type consequent functions	20 × 1	Consequent outputs are aggregated
Output layer	20 × 1	Aggregation and risk classification	1 × 3	Produces overall risk level: low, medium, or high

Source: **compiled by the authors**

The fuzzy component of the proposed ANFIS model is implemented through Gaussian membership functions that transform each of the five numerical input indicators into degrees of membership in the corresponding fuzzy sets. For each input variable, the membership value is determined by the Gaussian function, allowing gradual rather than binary transitions between linguistic risk states. The resulting membership degrees are combined through the fuzzy rule base, which contains 20 empirically defined rules obtained from historical data analysis, expert consultations, and clustering techniques. Each rule establishes a relationship between the identified risk conditions and the corresponding overall software project risk level. For example, a rule can express the condition that a high frequency of requirement changes combined with high defect density, frequent task delays, substantial budget overruns, and high team conflict corresponds to a high overall project risk. Conversely, predominantly low values of these indicators correspond to a low-risk state, while intermediate combinations produce a medium-risk assessment. Thus, fuzziness is introduced through continuous membership degrees and rule-based inference, while the ANFIS learning mechanism subsequently adjusts the membership-function and rule parameters using project data.

The neuro-fuzzy model was subsequently trained using a hybrid optimization algorithm combining the least-squares method and gradient descent, ensuring maximum precision and convergence stability. The hyperparameters were fine-tuned via grid search and 5-fold cross-validation, establishing an optimal configuration with a learning rate of 0.01, a fixed duration of 100 epochs, L2 regularization with a coefficient of 0.001, and a membership function width (σ) between 0.5 and 0.8. This fine-tuning established that the combination of Gaussian membership functions and 20 rules yielded the highest risk-classification accuracy of 94.7 %.

The parameter selection was based on the observed trade-off between classification accuracy, model complexity, and computational cost. The use of Gaussian membership functions with a width parameter σ in the range of 0.5-0.8 provided stable generalization, while the selected 20-rule knowledge base offered a balance between representational capability and training efficiency. The sensitivity analysis further showed that increasing the number of fuzzy rules from 15 to 25 increased training time by approximately 40 %, indicating that further expansion of the rule base may introduce additional computational costs without necessarily providing proportional improvements in classification performance. Thus, the selected configuration was adopted as a practical balance between accuracy, adaptability, and computational efficiency.

To further validate the model's structural resilience, a preliminary sensitivity analysis was conducted using the one-factor-at-a-time (OFAT) method, sequentially varying each input parameter by ±10% while maintaining others constant. This analysis revealed that fluctuations in requirement change frequency and task execution delays exerted the most substantial impact on overall risk prediction. Final validation on the allocated testing subset confirmed the model's high stability, demonstrating consistent system performance within a ±10 % variability threshold from the baseline parameter values, thereby verifying the efficacy of the ANFIS architecture for software development risk management.

RESEARCH RESULTS AND DISCUSSION

First of all, it should be noted that the ANFIS experimental model showed a high accuracy of risk classification at the level of 94.7 %. To provide a more comprehensive evaluation, the proposed model was additionally compared with classical fuzzy logic (FIS), the Analytic Hierarchy Process (AHP), Random Forest

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(RF), Extreme Gradient Boosting (XGBoost), and Support Vector Machine (SVM). All compared models were evaluated using the same testing dataset and under comparable experimental conditions. A complete list of quantitative results is given in Table 2.

As the presented results demonstrate, the proposed ANFIS model achieves the highest accuracy of risk classification (94.7 %) among the compared approaches, outperforming XGBoost (93.4%), Random Forest (92.1 %), SVM (90.8%), FIS (88.2%), and AHP (82.5 %). Although ANFIS requires a longer training time (120 s) than the compared machine learning models, its average decision-making time of 15 ms remains sufficiently low for practical risk assessment. Moreover, the ANFIS model demonstrates the highest adaptability to changes in input parameters (92.3 %), the highest percentage of correct identification of critical risks (96.1 %), and the greatest stability under incomplete data (89.5 %). These results indicate that the proposed ANFIS provides a balanced combination of classification accuracy, adaptability, robustness to incomplete data, and rapid decision-making, which supports its application to dynamic software development risk management.

The numerical results presented in Table 2 can be directly compared with the characteristics of contemporary risk assessment approaches discussed in the Related Works section. The proposed ANFIS model achieves a risk-classification accuracy of 94.7%, which is higher than the obtained results for XGBoost (93.4 %), Random Forest (92.1 %), SVM (90.8%), FIS (88.2 %), and AHP (82.5 %). In addition to classification accuracy, ANFIS demonstrates higher adaptability to changes in input parameters (92.3 %), more accurate identification of critical risks (96.1 %), and greater stability under incomplete data (89.5 %). These results indicate that, compared with conventional fuzzy and analytical approaches discussed in previous studies, the proposed model provides a more comprehensive combination of predictive accuracy and robustness, while its comparison with modern machine learning methods demonstrates competitive classification performance with additional advantages in handling uncertainty and incomplete risk information.

The higher classification accuracy of the ANFIS model can be attributed to its ability to combine adaptive learning with fuzzy representation of uncertain and incomplete risk information. Unlike conventional FIS, whose membership functions and rules are primarily determined by predefined expert knowledge, ANFIS can adjust its parameters using the available project data. Compared with conventional analytical approaches such as AHP, this allows the model to represent nonlinear relationships between risk factors more flexibly. The comparison with Random Forest, XGBoost, and SVM also indicates that the combination of data-driven parameter adaptation and fuzzy reasoning is particularly useful when software project risks are characterized by ambiguity, gradual transitions between risk levels, and incomplete information.

Given that the reported performance indicators were obtained under the experimental conditions defined in this study, they should be interpreted as empirical estimates rather than as evidence of statistical significance. Since the present study does not include repeated independent experiments sufficient for formal statistical hypothesis testing, the observed differences should therefore be considered indicative rather than statistically confirmed. Nevertheless, the consistent advantage of the ANFIS model across several evaluation indicators provides an empirical basis for its effectiveness, while formal statistical validation using confidence intervals and nonparametric tests will be considered in further studies.

Table 2. **Comparison of Risk-Assessment models by Key Metrics**

Metrics	ANFIS (proposed model)	Fuzzy logic (FIS)	Classic model (AHP)	Random Forest (RF)	XG Boost	SVM
Accuracy of risk classification, %	94.7	88.2	82.5	92.1	93.4	90.8
Average training time, sec	120	75	-	18	24	15
Average decision time, ms	15	9	45	3	4	5
Adaptability to change coefficient, %	92.3	65.8	30.5	88.6	90.2	84.7
Percentage of correct identification of critical risks, %	96.1	90.4	78.3	93.8	95.0	91.6
Stability of operation with incomplete data, %	89.5	77.2	50	86.4	88.1	82.9

Source: **compiled by the authors**

Beyond the comparative performance analysis, the scalability of the proposed model was also evaluated by increasing the dataset size from 600 to 1000 records. The model maintained classification accuracy above 93 %, while training time increased by approximately 45 %. This result indicates that the proposed ANFIS model remains effective as the data volume increases, although larger datasets require additional computational resources.

The adaptability analysis confirmed stable model performance under moderate variations in project-related input parameters, while larger deviations revealed the need for additional adjustment of the model parameters. Detailed results of the stability analysis for input variations from ±5 % to ±20 % are presented below.

During the experiments, certain anomalies and atypical situations were recorded, which are important for further improvement of the model. In particular, when using Gaussian membership functions, periodic spikes in classification error were noticed when processing certain groups of data containing very similar risk parameters. A detailed analysis of this anomaly made it possible to establish that the main cause is the overlap of belonging functions at very close values of risk parameters. To avoid such situations in the future, it is recommended to additionally adjust the width of the affiliation functions and carry out a finer calibration of these parameters.

It was also observed that the model shows a decrease in accuracy (up to 89 %) in cases where the input data contains more than 15 % of missing values. This is because neuro-fuzzy systems, although highly resistant to data incompleteness, are still sensitive to a significant amount of lost information. Further analysis confirmed that the use of more advanced data imputation techniques, such as k-NN or multivariate imputation, is able to improve this indicator.

The stability analysis demonstrated that the proposed ANFIS model maintains high classification accuracy under moderate variations in input parameters. The baseline accuracy was 94.7 %, while the model remained stable under input changes of ±5 %, ±10 %, ±15 %, and ±20 %, although larger deviations resulted in a gradual decrease in classification accuracy and an increase in computational time. These results indicate that the proposed model is sufficiently robust to moderate fluctuations in project-related risk parameters and can maintain reliable risk assessment under changing conditions.

The selected hyperparameter configuration provided a balanced trade-off between classification accuracy, model complexity, and computational efficiency. The detailed tuning procedure and parameter selection are described in the Research Methodology section, while the results presented here focus on the practical performance and robustness of the proposed ANFIS model.

The next step was to create a series of modified datasets in which each of the initial parameters was modified by a specified percentage ranging from ±5% to ±20 %. Variations were carried out uniformly for all input variables, such as the frequency of requirements changes, the number of defects, the number of delays in task execution, and other measures that affect the overall risk score. Each of these modifications created a separate scenario of system operation, and each scenario was tested using the same neuro-fuzzy ANFIS model as in the initial conditions.

At the stage of ±5 % change in input parameters, the results showed slight deviations in accuracy – the accuracy decreased from 94.7 % to 93.5%, which indicates a very high stability of the system in case of minor deviations. This allows us to conclude that the model has a high ability to self-adapt even with slight fluctuations in input parameters, which are typical for real operating conditions.

With an increase in variation to ±10 %, there was a slight further decrease in accuracy to the 92.3 % level. This is still quite high and allows the model to be considered effective for practical use in environments characterized by moderate variability of input data. It is worth noting that no significant anomalies or deteriorations were recorded at this level of variation other than a natural decrease in prediction accuracy.

A further increase in the range of parameter variability to ±15 % showed a more noticeable decrease in model accuracy to 89.1 %. This decrease in accuracy can be explained by an increase in the number of situations when the functions of belonging for different risk categories begin to overlap significantly. At this point, an increase in the number of false classifications that have been analyzed in detail has also been noticed. The analysis of these errors revealed that the main reason is a decrease in the effectiveness of belonging functions with an increase in the degree of overlap between fuzzy sets of risk categories. This effect indicates the need for additional optimization or revision of the parameters of fuzzy belonging functions to improve adaptability and maintain model accuracy in the face of significant data variations.

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The maximum level of parameter variation (±20%) showed the largest decrease in model accuracy – to the level of 85.4 %. This result indicates that with significant changes in the input data, the effectiveness of the model begins to noticeably decrease, which requires special attention when applied in projects where significant fluctuations in indicators are expected. It is worth noting that with such significant variations, there was also an increase in the average training time of the model by about 30 %, which indicates an increasing computational complexity in the process of adapting the model to new, complex scenarios.

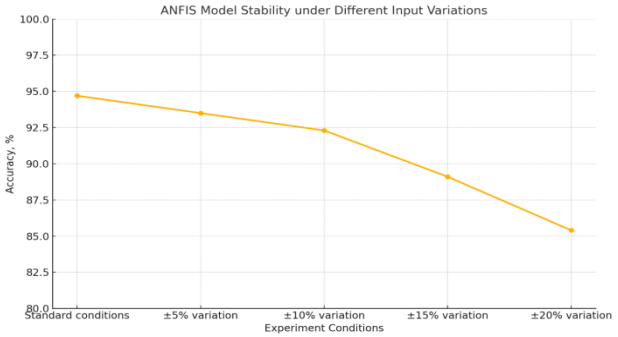


Fig 1. **Stability analysis of the ANFIS model accuracy under various input parameter variations**

***Source*: compiled by the authors**

The detailed outcomes of the stability analysis under various input parameter variations are visually summarized in Fig. 1, clearly illustrating the ANFIS model's robustness and consistency across different testing conditions.

The caption of Fig. 1 has been expanded to provide a more detailed explanation of the data presented. This includes clarifying the specific input parameter variations used in the stability analysis, explaining how accuracy is measured and represented in the chart, and explicitly stating the key takeaways from the figure. Fig. 1 illustrates the stability analysis of the model under various input variations. To improve clarity, the x-axis is labeled with specific variation levels (e.g., ±5 %, ±10 %, etc.),

The interpretation of the experiment results shows that the ANFIS model is able to demonstrate high stability and adaptability in a range of parameter variations up to ±10 %, which is quite typical for real practical situations. At the same time, under conditions of more significant deviations, the model still retains acceptable efficiency, although it requires additional adjustment and optimization to ensure maximum stability of operation. The results of this stage of the experiment allow us to formulate recommendations for the further use of the ANFIS model in practice, in particular regarding the limitations of its use in environments with highly variable indicators, as well as further steps to improve its performance in conditions of significant instability and uncertainty.

The results of additional analysis of the stability of the ANFIS model allow us to confirm its prospects for effective application in risk management in software development, at the same time indicating directions for further improvement and adaptation to complex and highly demanding operating conditions.

To further validate the robustness of the ANFIS model, additional experiments were conducted to evaluate its performance using various imputation methods for missing values, including mean/median substitution, k-nearest neighbors (k-NN), and regression-based imputation. The results indicated that employing k-NN imputation provided the highest accuracy improvement, reaching up to 91.7% when the dataset had up to 20 % missing data. In contrast, simple mean substitution showed lower performance with accuracy levels around 87.2%. These findings underscore the significance of choosing advanced imputation methods when dealing with incomplete data in practical risk management scenarios.

To ensure clarity, we provide the definitions and equations for the primary performance metrics used in this study:

– Accuracy (%) $= \frac{(TP+TN)}{(TP+TN+FP+FN)} \times 100\ \%$

– Adaptability (%): Proportion of correct classifications under ±10 % variation of input parameters.

– Stability with Incomplete Data (%): Classification accuracy when random subsets of input data are masked.

Where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

The results of the experimental study confirm the high efficiency of the proposed neuro-fuzzy ANFIS model in assessing risks during software development. The model demonstrates high accuracy, stability, and adaptability even under significant changes in input parameters. At the same time, the experimental results revealed several limitations that are not critical for the current application but should be considered when extending the model to more complex real-world software development environments.

Despite the demonstrated performance, several limitations should be considered when applying the

proposed ANFIS model in real-world software development environments. The increase in dataset size may lead to higher training time and computational requirements, as indicated by the scalability experiments, while substantially more complex projects may require additional input variables and a more extensive rule base. The model may also require additional adaptation in large-scale multi-team environments, where dependencies between teams, heterogeneous workflows, and coordination risks can introduce factors that are not fully represented by the current input variables. Furthermore, the model was evaluated under the experimental conditions defined in this study, and its performance may vary for projects with substantially different characteristics, organizational structures, or risk profiles. These limitations indicate that further research should focus on evaluating the model on larger and more heterogeneous datasets, extending the set of risk factors, and validating its performance in real multi-team software development environments.

From a practical implementation perspective, the proposed ANFIS model can be integrated into modern software project management platforms through an intermediate risk-assessment service. Data related to project tasks, defects, deadlines, workload, and other relevant risk factors can be obtained from platforms such as Jira, Azure DevOps, GitLab, or Redmine through their available interfaces and transferred to the ANFIS module for automated risk assessment. The resulting risk level can then be returned to the project management environment and used to support prioritization of critical tasks, identification of high-risk activities, and timely managerial intervention. Such an integration architecture would allow the proposed model to operate as an analytical component within existing project management workflows without requiring substantial changes to the underlying management platform.

CONCLUSIONS

The study demonstrates the significance of using the ANFIS neuro-fuzzy model to assess risks in software development processes under high uncertainty. The study confirmed the effectiveness of the neuro-fuzzy model in the context of decision-making under uncertainty. An important practical result was the high adaptability of the model, which significantly surpasses the traditional approaches presented in previous studies. This makes the proposed approach especially attractive for practical application in the context of frequent changes in software requirements.

The results obtained correlate with the study of Pei et al. [19], which emphasize the importance of using methods that allow decision-making in conditions of deep uncertainty. Their reinforcement learning approach has also shown high adaptability, but is more difficult to implement compared to the ANFIS neuro-fuzzy model. Comparing these results, it can be stated that ANFIS provides a more effective tool for prompt response to risks precisely due to lower computational complexity and a more understandable interpretation of the results obtained.

The results of this study are also supported by the work of Lesum et al. [13], which proved the importance of effective risk management to improve the overall performance of software projects. They emphasize the key role of adaptive models that can take into account the human factor and the dynamics of change, which is fully consistent with the results obtained in this study. At the same time, their research is based on risk management through organizational approaches and management decisions, while the proposed ANFIS model offers an automated solution capable of independently adapting to changing conditions.

Another important aspect is the work of Rosado et al. [22], who investigated the application of fuzzy logic to assess risks in business processes. They emphasize the importance of fuzzy models for integrating peer reviews and quantitative indicators, which is directly consistent with this study. However, the model proposed by them has a slightly lower adaptability to variable conditions compared to ANFIS, which indicates the advantage of using neuro-fuzzy approaches in dynamic conditions of software development.

The study by Basile et al. [1] also looks at risk management, but in the context of protecting software from unauthorized user intervention. While their work is more focused on security aspects, it also reaffirms the importance of automation and adaptability of solutions in the field of risk management. At the same time, the ANFIS model proposed in this study demonstrates a wider scope of application due to the ability to cover various types of risks, not limited to security issues.

Another critical area that warrants attention is the interpretability of risk management models. The results of this study demonstrated that although ANFIS offers significant advantages in accuracy and adaptability, ensuring clear interpretability of its outputs for stakeholders remains challenging. This finding aligns with Razzaq et al. [21], who emphasized the necessity of transparency in decision support systems, especially in high-stake environments. The study by Pikh, Senkivskyy, Sikora, Lysa, and Kudriashova [20]

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introduces a neuro-fuzzy approach that offers substantial practical value for decision-support in software engineering. By combining neural networks with fuzzy logic, the method effectively handles incomplete and dynamic data, enhancing the automation of risk-assessment processes in innovative IT projects. The authors also emphasize prospects for improving visualization and user-oriented interfaces to increase the interpretability and transparency of decision-making systems.

Another noteworthy aspect emerging from this study is the importance of computational performance trade-offs. Although the ANFIS model exhibited the highest accuracy among evaluated methods, it also required the most substantial computational resources during the training phase. This finding aligns with previous research by Zhao et al. [23], who emphasized that advanced fuzzy models typically demand significant computational power, particularly when dealing with large datasets. Thus, practical implementation of the ANFIS model in smaller-scale projects or those with limited computational resources might require further optimization or simplified configurations to maintain feasibility. Future research could explore model compression techniques or alternative optimization algorithms to mitigate computational demands while preserving acceptable accuracy levels.

The study validates both the feasibility and the high efficiency of employing the ANFIS neuro-fuzzy model for risk management tasks in software development under conditions of uncertainty. The findings highlight the superiority of the neuro-fuzzy approach compared to other widely used methods, particularly classical fuzzy techniques and the analytic hierarchy process. The proposed model demonstrated substantially improved outcomes in terms of accuracy and adaptability, thereby indicating strong potential for its broader application in risk management.

The principal advantages of the developed model include its adaptability to variations in input data (up to ±10 %), operational stability in the presence of incomplete datasets (up to 89.5 %), and rapid decision-making capability (15 ms). Nonetheless, the experiments revealed certain limitations, such as reduced accuracy under substantial data fluctuations (exceeding ±15 %) and increased computational complexity when handling datasets with a high proportion of missing values.

From a practical perspective, the proposed ANFIS model can be recommended for software projects of different scales, with the configuration and deployment approach adjusted to project complexity. For small projects with a limited number of risk factors, the model can be used with the existing compact rule base and a relatively small set of input parameters to support rapid risk assessment. For medium-sized projects, the model can be integrated with project management platforms and periodically updated using current project data, while for large and complex or multi-team projects, its application should include an expanded set of risk factors, additional adaptation of the fuzzy rule base, and continuous monitoring of model performance. Such differentiated use allows the model to retain its practical value while accounting for differences in project scale, complexity, data volume, and organizational structure.

A comparative analysis of the studies conducted by Pei et al., Lesum et al., Rosado et al., Basile et al., and Aregbesola et al. indicates that the ANFIS-based neuro-fuzzy approach can complement existing methods of intelligent decision-making, project governance, automated risk management, security risk assessment, and fuzzy evaluation of software design risks. Its ability to combine learning from historical data with the representation of uncertain expert knowledge makes it a promising solution for software development risk management and other application domains characterized by high uncertainty and dynamically changing parameters.

Considering the obtained results and identified limitations, future research should focus on optimizing fuzzy membership function parameters to mitigate errors under high variability of input data, as well as on developing enhanced methods for imputing missing values. Another important direction involves integrating behavioral aspects of teamwork and advancing the automation of risk management processes to minimize human influence.

Moreover, in light of challenges related to interpretability and computational resource demands, subsequent investigations should aim at designing optimized ANFIS configurations and developing clearer interpretability techniques, thereby improving practical applicability and stakeholder acceptance.

Overall, the developed ANFIS model demonstrates considerable advantages in decision-making under complex and ambiguous conditions of software project development and can serve as a

robust foundation for constructing more effective and sustainable risk management systems.

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Using artificial intelligence tools: Authors confirm that they did not use instrumental AI tools for writing this one work

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Адаптивна нейро-нечітка система для оцінки ризиків розробки програмного забезпечення в умовах невизначеності

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АНОТАЦІЯ

Актуальність. У статті розглядається проблема забезпечення ефективного управління ризиками в проектах з розробки програмного забезпечення в умовах значної невизначеності, неоднозначності та високої мінливості. Традиційні підходи до управління ризиками, що базуються на жорстких кількісних методах або точних математичних формулюваннях, часто виявляються неефективними через обмеженість вихідної інформації та високу суб'єктивність експертних оцінок, що підкреслює необхідність створення гнучких, динамічних та адаптивних моделей прийняття рішень. **Мета статті.** Метою дослідження є впровадження, розробка та валідація інноваційної структури прийняття рішень на основі адаптивної нейро-нечіткої системи виведення (ANFIS) для суттєвого підвищення як точності, так і адаптивності оцінки та класифікації ризиків у програмній інженерії. **Завдання.** Дослідження зосереджується на формалізації параметрів ризику програмних проектів за умов неповних даних, інтеграції можливостей навчання на основі даних нейронних мереж із механізмами нечіткої логіки в єдину архітектуру виведення, проведенні емпіричної оцінки з використанням наборів даних реальних проектів та виконанні порівняльного аналізу з традиційними методами управління ризиками. **Методи.** Запропонована система розроблена з використанням архітектури адаптивної нейро-нечіткої системи виведення (ANFIS), яка поєднує переваги адаптивного навчання нейронних мереж із можливостями нечіткої логіки щодо обробки невизначеності. Методологія реалізована та перевірена шляхом емпіричного моделювання та порівняльного тестування з класичними аналітичними методами з використанням реальних даних про проекти. **Наукова новизна.** Дослідження полягає у розробці та застосуванні гібридної нейро-нечіткої моделі, яка комплексно вирішує проблему невизначеності, автоматично враховує взаємозалежності ризиків та динамічно адаптується до змін у мінливих проектних середовищах, пропонуючи систему з значно вищою точністю порівняно з традиційними автономними нечіткими або статистичними рішеннями. **Практичне значення.** Запропонована система на основі ANFIS є надзвичайно придатною для використання в системах підтримки прийняття рішень, інструментах моніторингу програмних проектів та автоматизованих модулях управління ризиками для забезпечення безперервної, стійкої та автоматизованої класифікації ризиків в умовах динамічно мінливих або неповних даних. **Результати.** Емпірична оцінка з використанням наборів даних реальних проектів демонструє, що запропонована модель ANFIS суттєво перевершує традиційні нечіткі системи виведення та методи аналітичного ієрархічного процесу (AHP), досягаючи високої точності класифікації ризиків на рівні дев'яносто чотири цілих та сім десятих відсотків та демонструючи чудову стабільність у різних сценаріях вхідних даних. **Висновки.** Розроблена нейро-нечітка структура зарекомендувала себе як високоточне, гнучке та перспективне рішення для вдосконалення практик управління ризиками в програмній інженерії, успішно долаючи обмеження традиційних методологій щодо точності, адаптивності та гнучкості в мінливих середовищах.

Ключові слова: управління ризиками; невизначеність; нечітка логіка; модель прийняття рішень; нейро-нечітка модель; IT-технології

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***Research field*:** theory and practice of translation, ESP (German) teaching methodology, and linguacultural aspects of cross-cultural communication in the European educational space

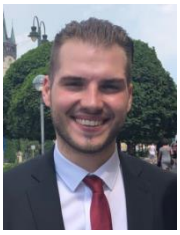
Жовтані Руслана Ярославівна – кандидат філологічних наук, доцент, завідувачка кафедри Міжнародних комунікацій. Ужгородський університет, пл. Народна, 3. Ужгород, 88000, Україна
Галузь досліджень: теорія та практика перекладу, методика викладання англійської мови для спеціалістів (англійської мови для спеціалістів) та лінгвокультурні аспекти міжкультурної комунікації в європейському освітньому просторі



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***Research field*:** historical and cultural prerequisites for tourism industry formation, methodology and design of scientific research, management and strategic development of hospitality and restaurant businesses, analysis of global religious tourism and pilgrimage trends, socio-historical evolution of regional ethno-political processes

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Галузь досліджень: історичні та культурні передумови формування туристичної галузі, методологія та проєктування наукових досліджень, управління та стратегічний розвиток готельного та ресторанного бізнесу, аналіз світових тенденцій релігійного туризму та паломництва, соціально-історична еволюція регіональних етнополітичних процесів



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Research field: information technologies, data protection, and decision-support methods in Aeronautical Information Management (AIM), with a focus on the development of intelligent models, fuzzy logic methods, data processing approaches, and digital solutions for improving the reliability, security, and efficiency of aviation information systems

Келемен Мартін – доктор філософії, асистент професора з Управління повітряним транспортом та безпеки, кафедра Льотної підготовки, Технічний університет у Кошицях, вул. Рампова 7. Кошице, 04001, Словаччина
Галузь досліджень: інформаційні технології, захист даних, методи підтримки рішень в управлінні аеронавігаційною інформацією (AIM) з акцентом на розробку інтелектуальних моделей, методів нечіткої логіки, підходів до обробки даних та цифрових рішень для підвищення надійності, безпеки, ефективність авіаційних інформаційних систем