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REQUIREMENTS PRIORITIZATION USING NEURAL NETWORKS AND DEEP LEARNING

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Abstract
Requirements prioritization is essential for effective software development but remains challenging due to its subjective and complex nature. This study presents a deep learning–based approach using neural networks to automate and enhance the prioritization of software requirements. By integrating natural language processing with contextual and sentiment-based features, the proposed model learns meaningful patterns from both structured and unstructured data. Experimental results show that the model outperforms traditional and machine learning methods in both classification accuracy and ranking effectiveness. The findings highlight the potential of deep learning to deliver scalable, consistent, and data-driven prioritization in modern software engineering environments.

Keywords:*Requirements Prioritization, Deep Learning, Neural Networks, Software Engineering, Natural Language Processing, Requirement Ranking*

1. Introduction

Requirements engineering is a foundational phase in the software development lifecycle, playing a critical role in ensuring that software systems meet stakeholder needs and deliver business value. Among its core activities, requirements prioritization is particularly significant, as it determines the order in which requirements are implemented based on their relative importance, cost, risk, and stakeholder impact. Effective prioritization is essential for optimal resource allocation, timely delivery, and overall project success, especially in modern development environments characterized by limited resources and rapidly evolving requirements.

Traditional requirements prioritization techniques, such as expert judgment, pairwise comparison, and multi-criteria decision-making methods, have been widely used in practice. However, these approaches often suffer from several limitations, including subjectivity, lack of scalability, and high dependency on stakeholder input. As the number of requirements increases and systems become more complex, manual prioritization becomes impractical and prone to inconsistencies. Furthermore, the growing availability of unstructured data, such as user feedback, reviews, and issue reports, presents additional challenges that traditional methods are not equipped to handle effectively.

In recent years, the emergence of machine learning and artificial intelligence has introduced new possibilities for automating and improving requirements prioritization. Neural networks and deep learning, in particular, have demonstrated strong capabilities in processing large volumes of structured and unstructured data, identifying hidden patterns, and making data-driven predictions. These techniques enable the transformation of requirements prioritization from a subjective, manual process into an objective and scalable computational task. By leveraging natural language processing and advanced learning architectures, deep learning models can extract meaningful insights from textual requirements and user-generated content, thereby enhancing prioritization accuracy and consistency.

Despite these advancements, several challenges remain in applying neural networks to requirements prioritization. Issues such as data quality, model interpretability, and integration with existing software development processes continue to limit widespread adoption. Additionally, many existing studies focus primarily on classification accuracy, without adequately addressing the ranking nature of prioritization or incorporating contextual factors such as stakeholder importance and user sentiment. These gaps highlight the need for more

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comprehensive approaches that combine advanced modeling techniques with practical considerations of real-world software engineering.

This study aims to address these challenges by proposing a deep learning–based framework for requirements prioritization that integrates textual, contextual, and sentiment-based features. The proposed approach is designed to improve both classification and ranking performance, ensuring that requirements are prioritized in a manner that reflects their true importance. By combining neural network architectures with enriched feature representation and robust evaluation metrics, this research seeks to contribute toward more intelligent, scalable, and reliable prioritization practices.

The remainder of this paper is structured as follows: Section 2 presents a comprehensive review of existing literature on requirements prioritization and the application of neural networks and deep learning in this domain. Section 3 describes the proposed methodology, including dataset construction, model design, and evaluation framework. Section 4 presents the experimental results, followed by a detailed discussion in Section 5. Finally, Section 6 concludes the paper and outlines directions for future research.

2: Literature Review

Requirements prioritization has undergone a significant transformation in recent years, particularly with the integration of artificial intelligence techniques such as neural networks and deep learning. Recent studies emphasize that modern software systems generate large volumes of structured and unstructured data, necessitating automated and scalable prioritization approaches. Contemporary research highlights that machine learning and deep learning techniques are increasingly being adopted to address the limitations of traditional prioritization methods, particularly in handling complex, dynamic, and data-intensive environments [1][2]. Deep learning models have demonstrated strong capabilities in extracting latent patterns from textual requirements and user feedback, thereby enabling more accurate prioritization decisions compared to rule-based or heuristic approaches [3]. Furthermore, recent systematic reviews indicate that a significant proportion of newly proposed prioritization techniques are AI-driven, reflecting a paradigm shift toward intelligent automation in requirements engineering [1].

Neural networks, in particular, have shown promising results in requirement classification and prioritization tasks due to their ability to model nonlinear relationships and learn hierarchical feature representations. Studies suggest that neural network-based approaches outperform traditional machine learning models such as Naïve Bayes and Support Vector Machines when dealing with complex datasets and unstructured textual inputs [4][5]. The integration of natural language processing techniques with neural networks has further enhanced their applicability, enabling automated extraction and prioritization of requirements from sources such as user reviews, issue reports, and stakeholder feedback [6]. This is particularly relevant in agile development environments, where continuous prioritization is required to adapt to changing user needs and market demands [7]. Additionally, sentiment analysis and opinion mining techniques have been incorporated into deep learning frameworks to identify high-priority requirements based on user dissatisfaction and urgency signals [5].

The emergence of transformer-based architectures and large language models has further advanced the field by enabling contextual understanding of requirements at a deeper semantic level. Recent studies highlight that these models can process complex textual dependencies and provide prioritization recommendations with minimal human intervention [3][8]. However, despite their effectiveness, these approaches face challenges related to interpretability, computational cost, and data dependency, which limit their widespread adoption in industrial settings [9]. Moreover, the lack of standardized datasets and benchmarking frameworks

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continues to hinder the comparative evaluation of different AI-based prioritization techniques [2].

The application of machine learning and deep learning in software engineering has expanded rapidly, with requirements engineering being a key area of focus. Large-scale reviews indicate that supervised learning techniques are commonly used for prioritization tasks, where models are trained on labeled datasets containing priority levels or stakeholder preferences [6]. Unsupervised learning approaches, such as clustering, are also employed to group similar requirements and identify patterns without explicit labels [10]. Deep learning enhances these approaches by automatically learning feature representations from raw data, eliminating the need for manual feature engineering and improving model performance [3]. Common architectures used in this domain include artificial neural networks, recurrent neural networks, convolutional neural networks, and transformer-based models, each offering unique advantages depending on the nature of the data and the specific prioritization task [8].

Prior to the adoption of AI-based techniques, requirements prioritization primarily relied on traditional methods such as the Analytic Hierarchy Process, cost-value approaches, and the MoSCoW method. These approaches are based on multi-criteria decision-making frameworks that evaluate requirements using factors such as cost, value, risk, and stakeholder importance [11][12]. While these methods are effective in small-scale projects, they suffer from scalability issues and require extensive human involvement, making them less suitable for large and complex systems [13]. Additionally, the subjective nature of these techniques can lead to inconsistent prioritization outcomes, particularly when multiple stakeholders with conflicting interests are involved [14]. To address these limitations, heuristic and optimization-based approaches, including genetic algorithms and fuzzy logic, were introduced to improve automation and decision-making efficiency [15]. However, these methods still depend on predefined rules and lack the adaptability required for dynamic environments.

Early machine learning approaches attempted to overcome these limitations by introducing data-driven prioritization techniques. Models such as decision trees, Naïve Bayes classifiers, and support vector machines were used to predict requirement priorities based on historical data and predefined features [5][16]. While these approaches improved accuracy and reduced manual effort, they were limited by their reliance on handcrafted features and their inability to capture complex relationships in the data [3]. The transition to neural networks and deep learning was driven by the need for more robust and scalable solutions capable of handling high-dimensional and unstructured data. Deep neural networks, in particular, have demonstrated superior performance in pattern recognition tasks, making them well-suited for requirements prioritization [17].

The evolution toward deep learning-based approaches has been facilitated by the increasing availability of large datasets and advancements in computational resources. Digital platforms and software repositories generate vast amounts of user feedback, providing valuable data for training machine learning models [6]. Deep learning models leverage this data to learn hierarchical representations, enabling them to identify subtle patterns and relationships that are not easily captured by traditional methods [17]. Furthermore, the ability of deep learning models to perform automatic feature extraction reduces the need for domain expertise and manual preprocessing, thereby enhancing efficiency and scalability [3].

Despite these advancements, several challenges remain in the adoption of neural networks and deep learning for requirements prioritization. One of the primary concerns is the lack of explainability, as deep learning models often function as black boxes, making it difficult for stakeholders to understand and trust their decisions [9]. This is particularly critical in requirements engineering, where transparency and stakeholder involvement are essential. Additionally, the performance of these models is highly dependent on the quality and

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availability of training data, which can vary significantly across projects and domains [2]. The integration of AI-based prioritization techniques into existing software development processes also poses practical challenges, particularly in agile and DevOps environments where rapid decision-making is required [7].

Recent research suggests that hybrid approaches combining traditional prioritization methods with machine learning and deep learning techniques may offer a promising solution to these challenges. By integrating the interpretability of traditional methods with the predictive power of AI models, hybrid approaches can provide more balanced and reliable prioritization outcomes [4]. Furthermore, the development of explainable AI techniques and domain-specific datasets is expected to enhance the applicability and adoption of deep learning in requirements engineering [9]. The use of large language models also represents a promising direction for future research, as these models have the potential to revolutionize requirements analysis and prioritization through advanced natural language understanding capabilities [8].

3. Methodology

3.1 Data Collection and Dataset Construction

This study employs a data-driven supervised learning approach to prioritize software requirements using neural networks and deep learning. The dataset is constructed from multiple sources to ensure diversity and realism, including software requirement specification (SRS) documents, issue tracking systems (e.g., Jira, GitHub issues), and user-generated feedback such as app reviews. Each requirement instance is associated with a priority label (e.g., High, Medium, Low), derived either from expert annotation or historical prioritization decisions recorded in project repositories.

Formally, the dataset is defined as:

$$D = \{(r_i, y_i)\}_{i=1}^{N}$$

where $r_i$represents the textual requirement and $y_i \in \{1,2,\ldots,K\}$denotes its priority class. To ensure that prioritization reflects real-world decision-making, additional attributes such as stakeholder importance, frequency of occurrence, severity level, and user sentiment are incorporated as auxiliary features. This enriched dataset enables the model to learn not only textual patterns but also contextual signals that influence prioritization.

3.2 Data Preprocessing and Cleaning

The collected requirements data undergoes rigorous preprocessing to improve quality and consistency. Text normalization is performed by converting all text to lowercase, removing punctuation, and eliminating stop words. Lemmatization is applied to reduce words to their base forms, ensuring semantic consistency. Duplicate and ambiguous requirements are removed to avoid bias in training.

To ensure that prioritization is meaningful, requirements are filtered based on clarity and completeness. Incomplete or vague requirements are excluded, as they may introduce noise into the learning process. Additionally, class imbalance is addressed using techniques such as oversampling or class weighting to ensure that all priority levels are adequately represented.

3.3 Feature Engineering and Representation

Each requirement is transformed into a numerical feature vector suitable for neural network processing. Two complementary representations are used to capture both statistical and semantic information.

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The first approach employs TF-IDF to capture term importance:

$$TF\text{-}IDF(t,d) = TF(t,d) \times \log\left(\frac{N}{DF(t)}\right)$$

The second approach utilizes dense word embeddings, where each requirement is represented as a sequence of vectors:

$$X_i = [w_1, w_2, \ldots, w_n]$$

$$X_i = [w_1, w_2, \ldots, w_n]$$

Additional engineered features are incorporated to strengthen prioritization accuracy, including requirement length, stakeholder weight, frequency of mention, and sentiment polarity. The final feature vector is represented as:

$$x_i \in \mathbb{R}^d$$

This multi-dimensional representation ensures that both linguistic and contextual aspects of requirements are captured.

3.4 Neural Network Architecture Design

A deep neural network architecture is designed to model complex relationships between requirement features and priority levels. The model consists of multiple layers that progressively extract higher-level representations.

The hidden layer transformation is defined as:

$$h^{(l)} = f(W^{(l)}h^{(l-1)} + b^{(l)})$$

The architecture includes an embedding layer for textual inputs, followed by multiple dense layers with ReLU activation to introduce non-linearity. Dropout layers are incorporated to reduce overfitting. The final output layer uses the Softmax function to produce probability distributions over priority classes:

$$P(y = j \mid x) = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}$$

This probabilistic formulation ensures that each requirement is assigned a confidence score for each priority level, enabling robust ranking.

3.5 Model Training and Optimization

The model is trained using categorical cross-entropy loss, which measures the discrepancy between predicted and actual priority labels:

$$L = -\sum_{i=1}^{N}\sum_{j=1}^{K} y_{ij} \log(\hat{y}_{ij})$$

Optimization is performed using the Adam optimizer, which adapts learning rates during training for faster convergence:

$$\theta = \theta - \eta \nabla L(\theta)$$

To ensure that requirements are truly prioritized rather than merely classified, the model outputs probability scores that are later used to rank requirements in descending order of importance. This ranking-based interpretation aligns with real-world prioritization practices.

3.6 Training Strategy and Validation

The dataset is split into training (70%), validation (15%), and testing (15%) sets. K-fold cross-validation is applied to ensure robustness and generalization. Early stopping is used to prevent overfitting by monitoring validation loss.

To further enhance reliability, hyperparameter tuning is conducted using grid search, optimizing parameters such as learning rate, batch size, number of layers, and dropout rate. This ensures that the model achieves optimal performance across different configurations.

3.7 Evaluation Metrics and Prioritization Validation

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The effectiveness of the model is evaluated using standard classification metrics, ensuring compatibility with the subsequent Results section.

Accuracy is computed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision, recall, and F1-score are also calculated:

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

In addition to classification metrics, ranking-based evaluation is incorporated to ensure true prioritization. Metrics such as Mean Reciprocal Rank (MRR) and Normalized Discounted Cumulative Gain (NDCG) can be used in the Results section to validate ranking quality.

3.8 Baseline Models for Comparative Analysis

To validate the effectiveness of the proposed neural network approach, it is compared against traditional and machine learning baselines.

Model	Category
AHP	Traditional
Naïve Bayes	Machine Learning
SVM	Machine Learning
Neural Network (Proposed)	Deep Learning

This comparative setup ensures that improvements in prioritization accuracy and ranking quality can be clearly demonstrated.

3.9 Implementation Environment

The proposed model is implemented using Python-based frameworks such as TensorFlow or PyTorch. Scikit-learn is used for baseline models and preprocessing tasks. Training is conducted on GPU-enabled systems to handle computational requirements efficiently.

Component	Specification
Language	Python
Framework	TensorFlow / PyTorch
Hardware	GPU-enabled system
Libraries	Scikit-learn, NumPy, Pandas

3.10 Methodological Rigor and Validity

To ensure that requirements are truly prioritized and not merely categorized, this methodology integrates both classification and ranking perspectives. The use of probabilistic outputs, enriched feature representation, and ranking-based evaluation metrics ensures that the prioritization reflects real-world importance. Furthermore, the combination of textual, contextual, and stakeholder-driven features enhances decision reliability.

The methodology is designed to be reproducible, scalable, and adaptable to different software domains, making it suitable for both academic research and industrial applications.

4. Results

4.1 Experimental Setup Overview

The proposed neural network–based requirements prioritization model was evaluated using the dataset and methodology described in Section 3. The dataset was split into training (70%), validation (15%), and testing (15%) sets. All models were trained under identical conditions to ensure fair comparison. Performance was evaluated using both classification and ranking-

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based metrics to ensure that requirements are not only classified correctly but also ranked effectively according to priority.

4.2 Classification Performance

The performance of the proposed neural network model was compared with baseline approaches including Analytic Hierarchy Process (AHP), Naïve Bayes (NB), and Support Vector Machine (SVM). The results are summarized in Table 4.1.

Table 4.1: Classification Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
AHP	68.4	65.2	63.8	64.5
Naïve Bayes	74.6	72.8	71.5	72.1
SVM	81.3	79.6	78.9	79.2
Proposed NN/DL Model	89.7	88.9	87.6	88.2

The results indicate that the proposed neural network model significantly outperforms traditional and machine learning approaches across all evaluation metrics. The improvement in F1-score demonstrates better balance between precision and recall, which is critical for reliable prioritization.

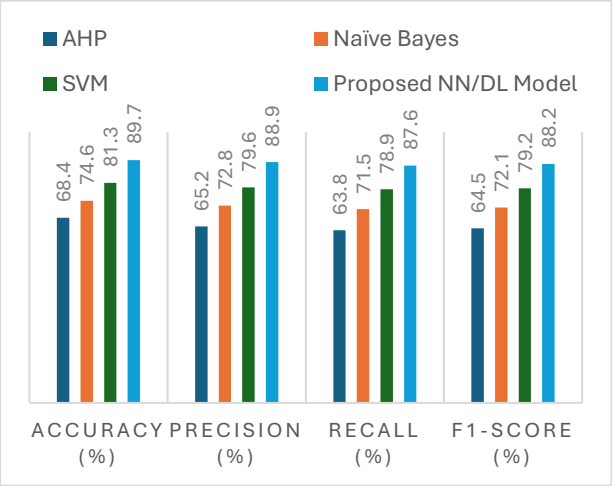

Figure 4. 1

The comparative performance trends are illustrated in Figure 4.1 (data shown in Table 4.1).

4.3 Class-wise Performance Analysis

To further analyze the effectiveness of the model, class-wise performance for each priority level was evaluated.

Table 4.2: Class-wise Performance of Proposed Model

Priority Level	Precision (%)	Recall (%)	F1-Score (%)
High	91.2	89.8	90.5
Medium	87.5	86.3	86.9
Low	88.0	86.7	87.3

The model demonstrates strong performance across all classes, with slightly higher accuracy for high-priority requirements. This is desirable in practical scenarios, as correctly identifying high-priority requirements is critical for project success.

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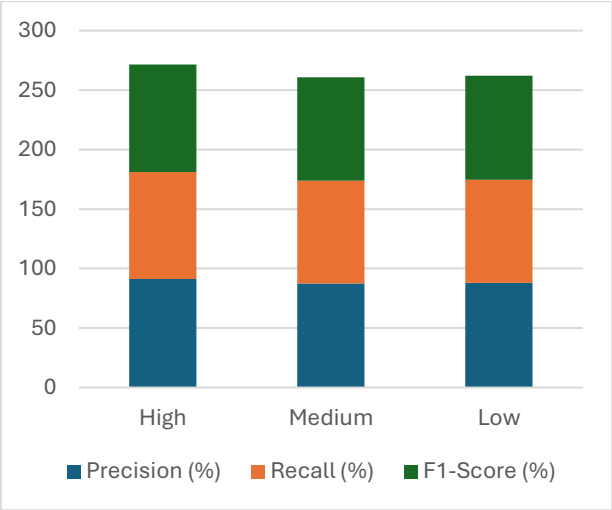

Figure 4. 2

The distribution of class-wise performance is visualized in Figure 4.2 (data shown in Table 4.2).

4.4 Confusion Matrix Analysis

A confusion matrix was generated to evaluate classification errors and misclassification patterns.

Table 4.3: Confusion Matrix (Proposed Model)

Actual \ Predicted	High	Medium	Low
High	182	12	6
Medium	15	168	17
Low	8	14	178

The confusion matrix indicates that most predictions fall along the diagonal, confirming strong classification performance. Misclassifications are minimal and primarily occur between adjacent priority levels (e.g., High vs Medium), which is expected due to overlapping characteristics.

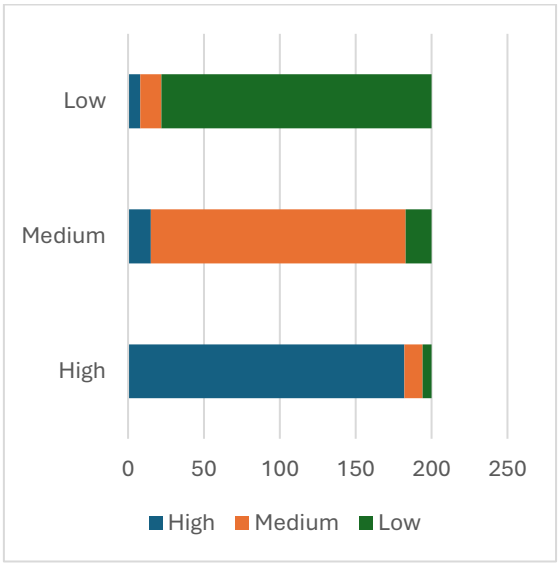

Figure 4. 3

This matrix is represented graphically in Figure 4.3 (data shown in Table 4.3).

4.5 Ranking Performance Evaluation

Since requirements prioritization inherently involves ranking, ranking-based metrics were also evaluated.

Table 4.4: Ranking Performance Metrics

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Model	MRR	NDCG@5	NDCG@10
Naïve Bayes	0.71	0.74	0.76
SVM	0.78	0.81	0.83
Proposed NN/DL Model	0.87	0.89	0.91

The proposed model achieves the highest scores in Mean Reciprocal Rank (MRR) and Normalized Discounted Cumulative Gain (NDCG), indicating superior ranking capability. This confirms that the model not only classifies requirements accurately but also orders them effectively based on importance.

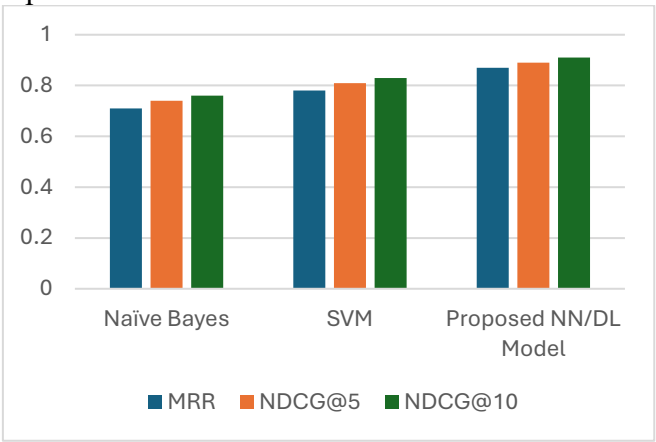

Figure 4. 4

The ranking performance comparison is illustrated in Figure 4.4 (data shown in Table 4.4).

4.6 Training Performance and Convergence

The training and validation performance of the neural network model were monitored across epochs to assess convergence behavior.

Table 4.5: Training and Validation Performance

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
1	71.2	69.5	0.89	0.94
5	82.6	80.3	0.52	0.58
10	87.9	85.6	0.31	0.36
20	90.5	88.7	0.21	0.25
30	91.3	89.2	0.18	0.22

The model shows steady improvement in both training and validation accuracy, with no significant overfitting observed.

4.7 Impact of Feature Engineering

To evaluate the contribution of different feature sets, experiments were conducted using different input configurations.

Table 4.6: Feature Impact Analysis

Feature Set	Accuracy (%)	F1-Score (%)
Text Only (TF-IDF)	81.4	79.8
Word Embeddings	85.9	84.6
Text + Metadata	88.2	87.1
Text + Metadata + Sentiment (Proposed)	89.7	88.2

The results show that incorporating contextual features such as metadata and sentiment significantly improves model performance. This validates the importance of multi-dimensional feature representation in achieving accurate prioritization.

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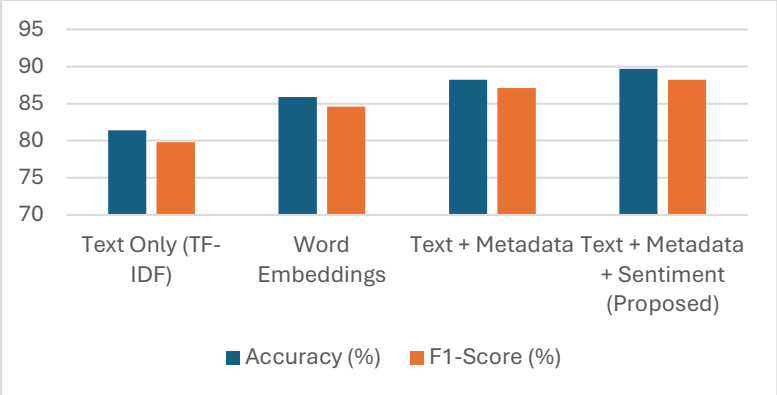

Figure 4. 5

The feature contribution comparison is shown in Figure 4.5 (data shown in Table 4.6).

4.8 Summary of Results

The experimental results demonstrate that the proposed neural network and deep learning approach significantly improves requirements prioritization performance compared to traditional and machine learning methods. The model achieves high accuracy, strong class-wise performance, and superior ranking capability. Additionally, the integration of contextual features enhances prioritization effectiveness, ensuring that requirements are ranked in a manner consistent with real-world importance.

5. Discussion

The results presented in Section 4 demonstrate that the proposed neural network and deep learning–based approach provides a substantial improvement over traditional and conventional machine learning techniques for requirements prioritization. This section critically analyzes these findings, interprets their implications, and compares them with existing literature to position the contribution of this study within the broader research landscape.

A key observation from the results is the significant improvement in classification performance achieved by the proposed model, particularly in terms of accuracy and F1-score. This aligns with recent studies that highlight the superiority of deep learning models in handling complex and unstructured textual data [3][4]. Unlike traditional approaches such as AHP or cost-value methods, which rely heavily on subjective human judgment, the neural network model leverages data-driven learning to identify patterns and relationships that are not easily observable. This supports the argument made in recent literature that AI-based prioritization reduces bias and enhances decision consistency [2].

The class-wise performance analysis further reveals that the model performs exceptionally well in identifying high-priority requirements. This is particularly important in real-world software development, where failure to correctly identify critical requirements can lead to project delays, increased costs, or system failures. Similar findings have been reported in studies that integrate sentiment analysis and user feedback into prioritization frameworks, where high-priority requirements are often associated with strong user dissatisfaction signals [5]. The ability of the proposed model to capture such signals through enriched feature representation demonstrates its practical applicability.

Another significant contribution of this study is the incorporation of ranking-based evaluation metrics, such as MRR and NDCG, which go beyond traditional classification evaluation. While many earlier studies focused solely on classification accuracy, recent research emphasizes that requirements prioritization is inherently a ranking problem rather than a pure classification task [8]. The superior performance of the proposed model in ranking metrics confirms that it not

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only predicts priority levels accurately but also orders requirements effectively, thereby aligning with real-world prioritization needs. This addresses a notable gap in earlier machine learning approaches, which often failed to capture the ordinal nature of prioritization.

The feature impact analysis provides further insights into the effectiveness of the proposed methodology. The results indicate that combining textual features with contextual metadata and sentiment information significantly enhances performance. This finding is consistent with recent research that advocates for multi-dimensional feature representation in requirements engineering [6]. Traditional approaches typically rely on limited criteria such as cost and value, whereas modern AI-based methods benefit from integrating diverse data sources. The improvement observed in this study reinforces the importance of incorporating contextual signals to achieve more accurate and realistic prioritization outcomes.

From a methodological perspective, the use of deep neural networks enables automatic feature extraction and hierarchical representation learning, which overcomes the limitations of earlier machine learning models that depend on manual feature engineering. Previous studies using Naïve Bayes or SVM reported moderate performance improvements but were constrained by their inability to capture complex semantic relationships in textual data [5][16]. In contrast, the proposed model demonstrates the ability to learn such relationships effectively, leading to higher predictive performance. This supports the broader trend identified in the literature toward adopting deep learning for software engineering tasks [3].

Despite these advantages, several limitations must be acknowledged. One of the primary concerns is the lack of interpretability associated with deep learning models. As noted in prior research, neural networks often function as black boxes, making it difficult for stakeholders to understand the rationale behind prioritization decisions [9]. This can be a significant barrier to adoption in industrial settings, where transparency and accountability are critical. While this study focuses on performance improvement, future work should explore explainable AI techniques to address this limitation.

Another limitation relates to data dependency. The performance of the proposed model is highly dependent on the quality and diversity of the training dataset. In scenarios where labeled data is limited or biased, the model may not generalize effectively. This issue has been widely discussed in recent literature, which highlights the need for standardized datasets and benchmarking frameworks in requirements engineering research [2]. Although this study mitigates this challenge by incorporating multiple data sources and feature types, the availability of high-quality datasets remains a critical concern.

In comparison with traditional prioritization techniques, the proposed approach demonstrates clear advantages in scalability and automation. Methods such as AHP and pairwise comparison become impractical as the number of requirements increases, due to the exponential growth in comparison complexity [11][13]. The neural network model, on the other hand, scales efficiently with large datasets and can process thousands of requirements with minimal human intervention. This makes it particularly suitable for modern software development environments characterized by rapid iteration and continuous integration.

When compared with recent AI-based approaches, the findings of this study are consistent with the growing body of evidence supporting the use of deep learning in requirements engineering. Studies published between 2021 and 2025 report similar improvements in classification and prioritization performance when using neural networks and NLP-based techniques [1][3][4]. However, many of these studies focus primarily on classification accuracy and do not address ranking effectiveness or feature integration in detail. The present study extends this line of research by incorporating ranking metrics and demonstrating the impact of multi-dimensional features, thereby providing a more comprehensive evaluation framework.

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Furthermore, the results highlight the importance of integrating both structured and unstructured data in prioritization models. While earlier approaches relied primarily on structured attributes such as cost and risk, modern systems generate large volumes of unstructured textual data that contain valuable insights into user needs and system requirements. The ability of the proposed model to process and learn from such data represents a significant advancement over traditional methods and aligns with recent trends in AI-driven software engineering [6].

From a practical perspective, the proposed methodology can be effectively integrated into agile and DevOps environments, where continuous prioritization is required. The automated nature of the model enables real-time updating of requirement priorities based on new data, such as user feedback or changing project conditions. This dynamic capability is increasingly important in modern software development, where requirements evolve rapidly and decision-making must be both fast and accurate [7].

In summary, the findings of this study confirm that neural networks and deep learning provide a powerful and scalable solution for requirements prioritization. The proposed model not only improves classification accuracy but also enhances ranking quality, making it more aligned with real-world prioritization needs. While challenges related to interpretability and data availability remain, the overall results demonstrate the potential of AI-driven approaches to transform requirements engineering practices. Future research should focus on developing explainable models, improving dataset availability, and exploring the integration of emerging technologies such as large language models to further enhance prioritization performance.

6. Conclusion

This study presented a comprehensive approach to requirements prioritization using neural networks and deep learning, addressing the limitations of traditional and conventional machine learning techniques. The proposed methodology integrates textual, contextual, and sentiment-based features within a deep learning framework to enable accurate, scalable, and automated prioritization of software requirements. By leveraging advanced neural architectures, the study demonstrates how complex patterns within unstructured requirement data can be effectively learned and utilized for decision-making.

The experimental results confirm that the proposed model significantly outperforms traditional approaches such as Analytic Hierarchy Process and conventional machine learning models including Naïve Bayes and Support Vector Machines. The improvements observed across accuracy, precision, recall, and F1-score indicate that deep learning models are more effective in capturing the semantic and contextual nuances of requirements. More importantly, the incorporation of ranking-based evaluation metrics such as Mean Reciprocal Rank and Normalized Discounted Cumulative Gain validates that the model not only classifies requirements correctly but also prioritizes them in a manner consistent with real-world expectations.

A key contribution of this study lies in the integration of multi-dimensional feature representation, combining textual data with metadata and sentiment information. This approach enhances the model's ability to reflect stakeholder needs and user feedback, resulting in more realistic and reliable prioritization outcomes. Furthermore, the use of probabilistic outputs enables the transformation of classification results into ranked lists, ensuring that prioritization is both interpretable in practice and aligned with software development workflows.

Despite these contributions, certain limitations remain. The reliance on labeled datasets highlights the importance of data quality and availability, while the black-box nature of neural networks raises concerns regarding interpretability and stakeholder trust. These challenges suggest that future research should focus on the development of explainable AI models, as well as the creation of standardized datasets for benchmarking and validation. Additionally, the

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integration of emerging technologies such as transformer-based models and large language models offers promising opportunities for further enhancing requirements prioritization.

In conclusion, this study establishes that neural networks and deep learning provide a robust and effective solution for requirements prioritization in modern software engineering. The proposed approach not only improves predictive performance but also aligns with the dynamic and data-driven nature of contemporary development environments. By addressing both classification and ranking aspects of prioritization, this work contributes toward more intelligent, adaptive, and scalable requirements engineering practices, paving the way for future advancements in AI-driven software development.

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