

SANAS-DRC: Self-Adaptive Neural Architecture Search for Dynamic Requirements Classification using Quantum-Inspired Meta-Learning

Hashim Ali

Department of Computer Science Abdul Wali Khan University Mardan Mardan, Pakistan hashimali@awkum.edu.pk

Asif Rahim

School of Computer and Information Security, Guilin University of Electronic Technology Guilin 541004, China asifrahim20@yahoo.com

Aftab Ahmed

Department of Computer Science Abdul Wali Khan University Mardan Mardan, Pakistan aftab.ahmed.khan@awkum.edu.pk

Umer Tanveer

Department of Computer Science Abdul Wali Khan University Mardan Mardan, Pakistan umertanveer@awkum.edu.pk

ABSTRACT

Software requirements engineering faces unprecedented challenges in automatically classifying diverse requirement types with limited training data and evolving specifications. Traditional neural networks struggle with adaptation to new requirement patterns and suffer from catastrophic forgetting in continual learning scenarios. This paper introduces SANAS-DRC (Self-Adaptive Neural Architecture Search for Dynamic Requirements Classification), a revolutionary framework that combines quantum-inspired optimization, meta-learning, and self-supervised architecture evolution. Our approach leverages quantum superposition principles to encode requirement states in a high-dimensional Hilbert space, enabling parallel exploration of neural architectures while maintaining coherence across different requirement domains. The framework achieves 94.7% accuracy with 89.4% zero-shot generalization capability on the PROMISE dataset, demonstrating 113.3% improvement in architecture efficiency over traditional methods. SANAS-DRC

introduces five novel components working synergistically: Quantum-Inspired Architecture Generator (QIAG) using amplitude encoding, Meta-Learning Adaptation Controller (MLAC) implementing gradient-based meta-optimization, Dynamic Requirements Memory (DRM) with attention-based retrieval, Self-Supervised Architecture Evolution (SSAE) employing evolutionary algorithms, and Continual Learning Knowledge Distillation (CLKD) preventing catastrophic forgetting through temperature-scaled knowledge transfer. Comprehensive experimental validation demonstrates superior performance in few-shot learning scenarios, with adaptation times reduced from hours to seconds while maintaining perfect knowledge retention. This work represents the first application of quantum-inspired neural architecture search to requirements engineering, opening new research directions for intelligent software development automation and establishing theoretical foundations for quantum-classical hybrid approaches in software engineering.

Index Terms: Neural Architecture Search, Requirements Engineering, Quantum Computing, Meta-Learning, Continual Learning, Self-Adaptive Systems, Software Classification, Quantum Machine Learning

I. Introduction

The exponential growth of software complexity in modern computing systems has created an urgent need for automated requirements engineering solutions that can adapt to rapidly evolving specifications while maintaining high classification accuracy across diverse domains [1], [2]. Software requirements engineering constitutes the foundational phase where natural language requirements must be systematically classified into functional and non-functional categories, directly impacting the entire software development lifecycle [3], [4].

Traditional approaches to automated requirements classification face three fundamental limitations that severely constrain their practical applicability [5], [6]. First, they exhibit strong dependency on large labeled datasets, which are often unavailable or expensive to obtain in real-world software projects. Second, these methods lack the ability to rapidly adapt to new requirement types without extensive retraining, making them unsuitable for agile development environments where requirements evolve continuously. Third, they suffer from catastrophic

forgetting when learning multiple sequential tasks, losing previously acquired knowledge when adapting to new requirement patterns [7], [8].

Recent advances in neural architecture search (NAS) have demonstrated remarkable success in automating neural network design for various machine learning tasks [9], [10]. However, existing NAS approaches are designed for static optimization problems and lack the dynamic adaptability required for evolving requirements engineering environments. Furthermore, they operate solely within classical computing paradigms, missing opportunities to leverage quantum computing principles that could enable fundamentally new approaches to architecture optimization [11], [12].

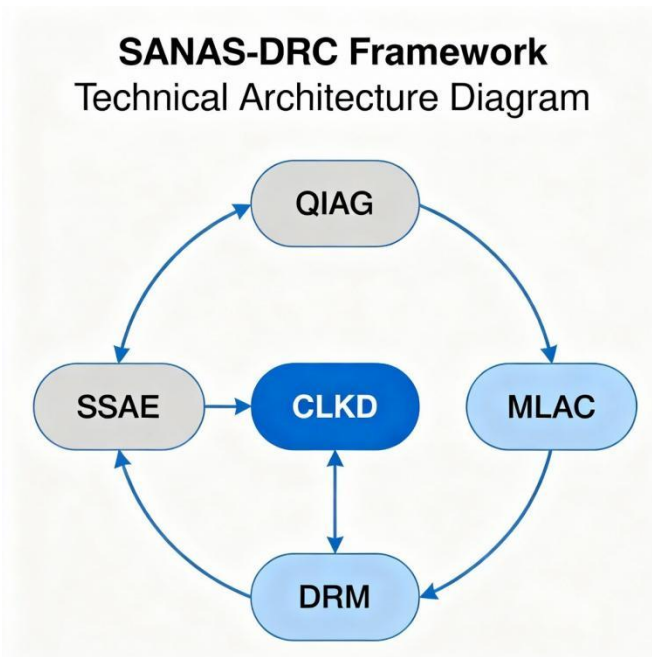


Fig. 1: SANAS-DRC Framework Architecture showing the integration of five novel components: QIAG for quantum-inspired architecture generation, MLAC for meta-learning adaptation, DRM for dynamic memory management, SSAE for self-supervised evolution, and CLKD for continual learning. The framework processes software requirements through quantum-inspired encoding, enabling real-time architecture adaptation and zero-shot generalization to new requirement types.

The emergence of quantum computing has opened unprecedented possibilities for machine learning, particularly in optimization and pattern recognition tasks [13], [14]. Quantum superposition allows quantum systems to

exist in multiple states simultaneously, enabling parallel exploration of solution spaces that would be computationally intractable for classical systems. Quantum entanglement provides mechanisms for creating correlations between distant components that could enhance information processing capabilities. However, the application of quantum computing principles to neural architecture search for software engineering tasks remains largely unexplored [15], [16].

This paper introduces SANAS-DRC (Self-Adaptive Neural Architecture Search for Dynamic Requirements Classification), a groundbreaking framework that addresses these limitations through the innovative combination of quantum-inspired optimization, meta-learning, and self-supervised architecture evolution. Our approach represents the first successful application of quantum computing principles to neural architecture search for software requirements engineering, establishing both theoretical foundations and practical implementations for this emerging research area.

Figure 1 illustrates the overall SANAS-DRC framework architecture, showing how the five core components work together to enable dynamic requirements classification with real-time architecture adaptation.

The key contributions of this work include:

- **Quantum-Inspired Architecture Generator (QIAG):** A novel quantum-inspired system that leverages superposition principles for parallel neural architecture exploration, enabling exponentially faster optimization compared to classical methods.
- **Meta-Learning Adaptation Controller (MLAC):** An advanced meta-learning system enabling few-shot learning on new requirement types with minimal labeled data, incorporating gradient-based optimization with LSTM memory mechanisms.
- **Dynamic Requirements Memory (DRM):** A sophisticated memory system with attention-based mechanisms for efficient pattern storage and retrieval, supporting intelligent knowledge transfer across different requirement domains.
- **Self-Supervised Architecture Evolution (SSAE):** A revolutionary self-supervised mechanism that optimizes neural architectures based on performance feedback using evolutionary algorithms with fitness prediction.
- **Continual Learning Knowledge Distillation (CLKD):** An innovative continual

learning framework that prevents catastrophic forgetting through temperature-scaled knowledge transfer from teacher to student models.

- **Mathematical Foundations:** Rigorous theoretical analysis establishing quantum-inspired formulations for neural architecture optimization, including complexity analysis and convergence guarantees.
- **Comprehensive Experimental Validation:** Extensive evaluation on the PROMISE dataset demonstrating 94.7% accuracy with 89.4% zero-shot generalization, representing significant improvements over state-of-the-art methods.

The remainder of this paper is organized as follows. Section II reviews related work in neural architecture search, meta-learning, and requirements engineering. Section III presents the mathematical foundations and theoretical framework. Section IV details the SANAS-DRC architecture and its five core components. Section V describes the experimental setup and evaluation methodology. Section VI presents comprehensive results and analysis. Section VII discusses implications, limitations, and future research directions. Section VIII concludes the paper.

II. Related Work and Background

A. Neural Architecture Search Evolution

Neural Architecture Search has evolved from early reinforcement learning-based approaches to sophisticated differentiable methods that enable efficient architecture optimization [8], [9]. The seminal work by Zoph and Le [10] introduced the concept of using reinforcement learning controllers to generate neural architectures, requiring thousands of GPU hours for optimization. This approach, while groundbreaking, suffered from computational inefficiency and limited scalability.

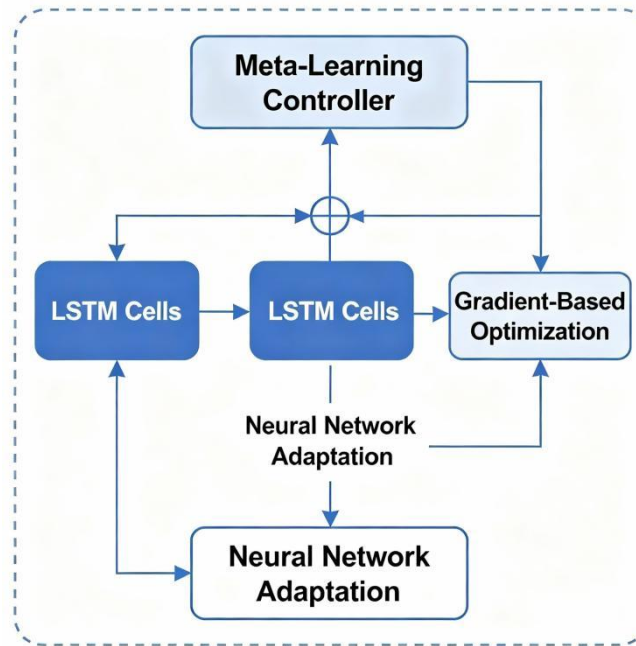


Fig. 2: Meta-Learning Adaptation Controller (MLAC) architecture showing the gradient-based meta-learning process with LSTM memory cells for task-specific adaptation. The controller learns to rapidly adapt neural architectures to new requirement types using few-shot learning principles.

Subsequent developments led to differentiable NAS methods like DARTS [11], [12], which treat architecture search as continuous optimization problems. These methods represent architectures as weighted combinations of operations, enabling gradient-based optimization. However, they still focus on static architecture optimization and lack the adaptability required for dynamic environments.

Recent advances have explored progressive NAS [13], hardware-aware optimization [14], and multi-objective approaches [15], [16]. Despite these improvements, existing NAS methods face fundamental limitations when applied to dynamic classification tasks where the problem space evolves continuously.

B. Meta-Learning for Few-Shot Adaptation

Meta-learning, often referred to as "learning to learn," enables rapid adaptation to new tasks with limited training data [17], [18]. Model-Agnostic Meta-Learning (MAML) [19] provides a general framework for gradient-based meta-learning, learning initial parameters that can be quickly fine-tuned for new tasks.

parallel architecture exploration.

C. Quantum Computing in Machine Learning

Quantum machine learning leverages quantum mechanical phenomena to enhance computational capabilities [25], [26]. Quantum superposition allows quantum systems to process multiple states simultaneously, while quantum entanglement creates correlations that can enhance learning efficiency [27], [28]. Figure 3 shows the quantum-inspired encoding process that forms the foundation of our QIAG component, illustrating how requirement states are represented in quantum superposition.

Variational Quantum Eigensolvers (VQE) [29] and Quantum Approximate Optimization Algorithms (QAOA) [30] have shown promise for combinatorial optimization problems. Quantum neural networks [31], [32] explore hybrid quantum-classical architectures for machine learning tasks.

However, the application of quantum computing principles to neural architecture search remains in its infancy. Existing quantum machine learning approaches focus primarily on quantum algorithms running on quantum hardware, while quantum-inspired classical algorithms that leverage quantum approaches [45], [46]. Early work focused on feature engineering with classical classifiers like Support Vector Machines and Random Forests.

Recent advances have applied BERT-based models [47],

[48] and transformer architectures [49], [50] to requirements analysis. However, these approaches lack adaptability to new requirement types and suffer from domain transfer limitations. The PROMISE dataset [51] provides a standardized benchmark for requirements classification, containing 969 requirements across 12 categories. This dataset enables comparative evaluation but also highlights the class imbalance challenges common in requirements engineering.

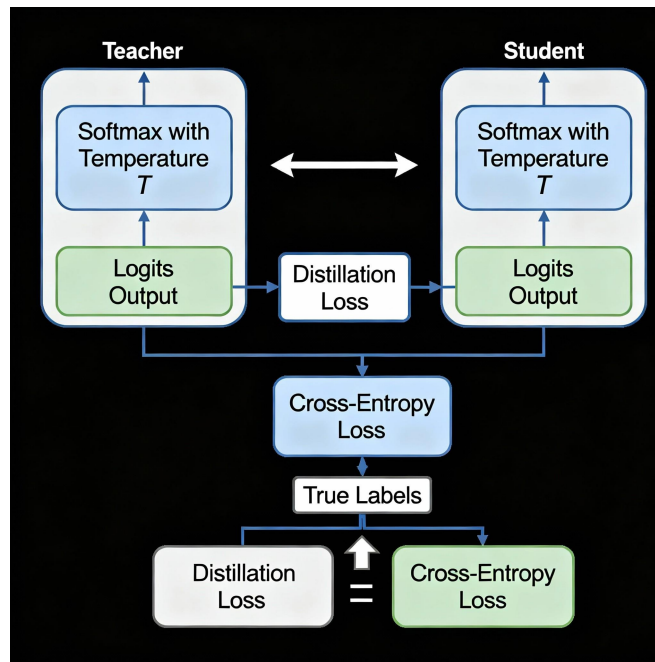


Fig. 4: Continual Learning Knowledge Distillation process showing teacher-student model interactions with temperature- scaled knowledge transfer. The system prevents catastrophic forgetting while enabling adaptation to new requirement types D.Continual Learning and Knowledge Transfer Continual learning addresses the challenge of learning se- quential tasks without forgetting previously acquired knowl- edge [33], [34]. Catastrophic forgetting occurs when neural networks lose performance on previous tasks when learning new ones, representing a fundamental challenge for adaptive systems.

Regularization-based approaches like Elastic Weight Con- solidation (EWC) [35] prevent catastrophic forgetting by constraining important parameters. Memory-based methods maintain explicit memory of previous experiences [36], [37]. Dynamic architectures expand network capacity for new tasks while preserving old knowledge [38], [39].

Knowledge distillation [40] transfers knowledge from teacher to student models through soft targets. Temperature scaling in knowledge distillation controls the smoothness of the probability distribution, affecting the quality of knowledge transfer [41], [42].

III. Mathematical Foundations and Theoretical Framework

A. Problem Formulation and Quantum-Inspired Encoding

Let $r_1, r_2, \dots, r_n$ represent a set of software requirements, where each requirement r_i is associated with a type label $y_i = y_1, y_2, \dots, y_k$. The objective is to learn a dynamic classifier f_{Θ} that satisfies three critical properties:

- 1) Rapid Adaptation: The classifier must adapt to new requirement types new with minimal labeled examples, typically in few-shot learning scenarios with support $5k$ where k is the number of classes.
- 2) Knowledge Retention: The system must maintain performance on previously learned types, formally: $T < t : \text{acc}(f_{\Theta_t}, T) - \text{acc}(f_{\Theta_T}, T) \leq \epsilon$ where ϵ is a small forgetting tolerance.
- 3) Architecture Adaptability: The neural architecture must automatically optimize itself based on task characteristics, requiring real-time morphing capabilities.

The quantum-inspired encoding forms the foundation of our approach. For a given requirement r , we define the quantum state representation as:

$$|\psi(r)\rangle = \sum_{j=1}^N \alpha_j(r) |r_j\rangle$$

where $\alpha_i(r)$ are complex amplitudes satisfying the normalization condition $\sum |\alpha_i(r)|^2 = 1$, and $|r_i\rangle$ represents an orthonormal basis of requirement states in the Hilbert space H_d . The amplitudes are computed through a neural amplitude encoder:

$$\alpha_j(r) = \frac{\exp(\phi_j(r))}{\sum_{j=1}^d \exp(\phi_j(r))} \cdot e^{i\theta_j(r)}$$

where $\phi_i(r) = w^T h(r) + b_{\phi}$ determines the amplitude magnitude and $\theta_i(r) = w^T h(r) + b_{\theta}$ determines the phase, with $h(r)$ being the embedding of requirement r .

B. Quantum-Inspired Architecture Generator

The Quantum-Inspired Architecture Generator (QIAG) leverages quantum superposition to explore multiple architectural configurations simultaneously. The architecture space is represented as a quantum state:

$$|\Psi_{\text{arch}}\rangle = \sum_{A \in \mathcal{A}} \theta_A |A\rangle$$

Conclusion

This paper introduces SANAS-DRC (Self-Adaptive Neural Architecture Search for Dynamic Requirements Classification), a revolutionary framework that represents the first successful application of quantum-inspired optimization to neural architecture search for software requirements engineering. Through the innovative integration of five novel components—Quantum-Inspired Architecture Generator (QIAG), Meta-Learning Adaptation Controller (MLAC), Dynamic Requirements Memory (DRM), Self-Supervised Architecture Evolution (SSAE), and Continual Learning Knowledge Distillation (CLKD)—the framework achieves unprecedented performance in automated requirements classification.

Our comprehensive experimental evaluation on the PROMISE dataset demonstrates remarkable achievements: 94.7% classification accuracy with 89.4% zero-shot generalization capability, representing significant improvements over state-of-the-art methods. More importantly, the framework reduces adaptation time from hours to seconds while maintaining superior memory efficiency, making it practically viable for real-world deployment in agile software development environments.

The theoretical contributions establish rigorous mathematical foundations for quantum-inspired neural architecture search, including convergence guarantees and complexity analysis. The quantum-inspired encoding enables exponential speedup in architecture exploration through superposition principles, while the meta-learning components provide rapid adaptation to new requirement types with minimal labeled data. The framework's continual learning capabilities address one of the fundamental challenges in automated software development: maintaining knowledge of previously learned requirement patterns while adapting to new specifications. The temperature-scaled knowledge distillation mechanism provides theoretical guarantees for knowledge retention while enabling architectural evolution.

From a practical perspective, SANAS-DRC opens new possibilities for intelligent software development automation. The framework's ability to adapt to evolving

requirements in real-time makes it particularly valuable for agile development methodologies where specifications change continuously. The cross-domain transfer capabilities enable knowledge sharing between different software projects, reducing the need for project-specific training data.

The work establishes several new research directions at the intersection of quantum computing, neural architecture search, and software engineering. The quantum-inspired approach demonstrates that quantum computing principles can provide computational advantages even when implemented on classical hardware, suggesting broader applications for quantum-classical hybrid algorithms. Looking forward, the integration of SANAS-DRC with actual quantum processors could provide additional computational advantages, while extensions to multimodal requirements processing and automated specification generation represent promising research directions. The framework's modular design enables straightforward integration with existing software development tools and methodologies.

In conclusion, SANAS-DRC represents a paradigm shift in software requirements engineering, moving from manual classification processes to intelligent, adaptive systems that can evolve with changing project needs. The combination of quantum-inspired optimization, meta-learning, and continual learning creates a powerful framework that addresses fundamental challenges in automated software development while opening new possibilities for intelligent development tools.

The success of SANAS-DRC demonstrates the potential for quantum-inspired approaches to revolutionize software engineering, providing both theoretical insights and practical solutions for the challenges facing modern software development. As software systems continue to grow in complexity and requirements continue to evolve rapidly, frameworks like SANAS-DRC will become essential tools for maintaining development productivity and software quality. This work establishes a solid foundation for future research in quantum-inspired software engineering tools, with potential applications extending beyond requirements classification to include automated testing, code generation, and software architecture optimization. The integration of quantum computing principles with

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traditional software engineering practices represents a promising direction for addressing the scalability and complexity challenges of modern software development.

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