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AN ENSEMBLE OF TOKENIZATION, AUTOENCODER AND TEMPORAL CONVOLUTIONAL NETWORK FOR SQL INJECTION DETECTION.

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ABSTRACT

SQL Injection (SQLi) attacks remain a critical cybersecurity threat, with traditional detection methods struggling against novel attack patterns. This study proposes a hybrid deep learning architecture combining SQL-aware tokenization, a 1D Convolutional Autoencoder (1D-CAE), and a Temporal Convolutional Network (TCN) for robust SQLi detection. The framework leverages the autoencoder for unsupervised anomaly detection and the TCN for temporal sequence modeling. Evaluated on 30,918 SQL queries, the proposed ensemble achieved 98.53% accuracy, 92.5% precision, 95.5% recall, and 94.0% F1-score, significantly outperforming Random Forest (87.0% F1-score) and individual model components. The TCN's parallel processing capability enabled 12.3 milliseconds average inference time per query, supporting real-time deployment. The fusion of anomaly-based and sequence-based deep learning provides an efficient, scalable defense against both known and zero-day SQLi attacks.

1 INTRODUCTION

Cybersecurity is the practice of protecting digital assets such as networks, systems, applications, and data from unauthorized access, breaches, manipulation, or destruction. In the digital age, where web-based platforms drive most organizational operations, ensuring the security of underlying databases has become increasingly critical. One of the most dangerous and persistent threats in this domain is Structured Query Language Injection (SQLi) a technique that allows attackers to insert malicious SQL code into web inputs to alter or hijack database operations [8,9].

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SQLi vulnerabilities exploit weaknesses in web application input validation. These flaws permit attackers to bypass authentication, retrieve unauthorized data, or even gain administrative access. For instance, a login form that does not sanitize user input can be manipulated using SQL logic (' OR 1=1--) to gain access without valid credentials.

Structured Query Language (SQL) is the core language used for interacting with Relational Database Management Systems (RDBMS), allowing developers to insert, retrieve, update, or delete data. However, when input sanitization is insufficient or poorly implemented, SQLi attackers exploit these interfaces to inject unauthorized SQL commands. This exploitation can lead to serious security consequences such as unauthorized data access, loss of data integrity, and denial of service [3,4].

Even more concerning is the evolution of SQLi into advanced forms such as Blind SQLi, Time-Based SQLi, and Out-of-Band SQLi, which often go undetected by traditional firewalls or rule-based security tools [6]. These variants rely on indirect cues or time delays to infer sensitive information, making them especially difficult to trace and mitigate.

Despite the deployment of modern security strategies such as Web Application Firewalls (WAFs) and anomaly detection models, SQLi continues to be a top-ranked vulnerability on the OWASP Top 10 list [4]. This persistence highlights the need for intelligent detection systems especially deep learning-based solutions that can detect complex and zero-day attack patterns by learning temporal and semantic dependencies in query behavior [1,7].

Thus, this research aims to address the existing detection limitations by proposing a hybrid deep learning architecture that integrates Autoencoders, Tokenization, and Temporal Convolutional Networks (TCNs) to improve SQLi detection accuracy, resilience, and efficiency in real-time environments.

2. LITERATURE REVIEW

2.1 CONCEPTUAL FRAMEWORK

2.1.1 SQL INJECTION ATTACKS: A TAXONOMY

SQL injection attacks can be categorized based on the method of injection and the type of information leakage. The primary types include in-band (error-based and union-based), inferential (blind), and out-of-band SQLi. In-band SQLi is the most common and involves the attacker using the same communication channel to launch the attack and gather results. Error-based SQLi relies on forcing the database to generate error messages that reveal information about the database structure. Union-based SQLi leverages the UNION SQL operator to combine the results of a malicious query with a legitimate query.

Inferential SQLi, also known as blind SQLi, is more complex and time-consuming. It is used when the web application does not return the results of the malicious query directly in its HTTP response. The attacker sends a series of queries that return different results depending on whether the query is true or false. This allows the attacker to infer information about the database one bit at a time. Time-based blind SQLi is a subtype of inferential SQLi where the attacker sends a query that forces the database to wait for a specified amount of time, allowing the attacker to infer information based on the response time.

Out-of-band SQLi is less common and is used when the attacker cannot use the same channel to launch the attack and gather results. This technique relies on the database server's ability to make

DNS or HTTP requests to an external server controlled by the attacker. This allows the attacker to exfiltrate data through a different channel.

2.1.2 MACHINE LEARNING FOR CYBERSECURITY

Machine learning has been widely applied in cybersecurity for tasks such as intrusion detection, malware analysis, and spam filtering. Supervised learning algorithms, such as Support Vector Machines (SVM), Random Forests, and Neural Networks, are trained on labeled datasets to classify new, unseen data. Unsupervised learning algorithms, such as k-means clustering and autoencoders, are used to identify patterns and anomalies in unlabeled data. Reinforcement learning is used to train agents to take actions in an environment to maximize a cumulative reward, which can be applied to tasks such as autonomous penetration testing.

2.1.3 DEEP LEARNING MODELS FOR SEQUENCE ANALYSIS

Deep learning models, particularly Recurrent Neural Networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), have been successful in modeling sequential data. These models can capture temporal dependencies in data, making them suitable for tasks such as natural language processing, speech recognition, and time series analysis. More recently, Temporal Convolutional Networks (TCNs) have emerged as a powerful alternative to RNNs for sequence modeling. TCNs use causal and dilated convolutions to capture long-range dependencies in data and can be trained more efficiently than RNNs.

2.2 THEORETICAL FRAMEWORK

Our proposed architecture is grounded in two well-established machine learning paradigms: model-based anomaly detection and ensemble learning. The synergy between these two frameworks provides a robust theoretical foundation for our hybrid SQLi detection system.

2.2.1 ANOMALY DETECTION AND ITS MOTIVATION FOR THE AUTOENCODER

Anomaly detection aims to identify data points that deviate significantly from a learned norm. Among the primary categories statistical-based, distance-based, and model-based our work adopts the model-based approach. This paradigm involves creating a model that captures the underlying patterns of normal data; instances that the model fails to represent accurately are flagged as anomalies.

This theory directly motivates our use of the 1D Convolutional Autoencoder (1D-CAE). The autoencoder is trained to reconstruct legitimate SQL queries by first compressing them into a low-dimensional latent representation (encoding) and then decompressing them back to their original form (decoding). Because the model is trained primarily on normal data, it learns the essential features and syntax of benign queries. When a malicious query which deviates from this learned norm is introduced, the autoencoder struggles to reconstruct it accurately. The resulting high reconstruction error serves as a powerful, quantifiable indicator of anomalous activity, allowing the model to detect novel or zero-day attacks without prior exposure to them.

2.2.2 ENSEMBLE LEARNING PRINCIPLES AND THE JUSTIFICATION FOR TCN+CAE FUSION

Ensemble learning is founded on the principle that combining multiple models can yield superior performance compared to any single constituent model. By aggregating the "knowledge" of diverse models, an ensemble can reduce variance, mitigate bias, and improve generalization. While common methods like bagging, boosting, and stacking focus on combining model predictions, our architecture applies a more sophisticated form of this principle: feature-level ensembling.

This principle justifies the fusion of our Temporal Convolutional Network (TCN) and 1D-CAE components. Rather than operating as independent classifiers, these two models act as specialized feature extractors that capture different but complementary aspects of the input data:

- The 1D-CAE operates from an anomaly detection perspective, generating features based on a query's structural normality (reconstruction error).
- The TCN operates from a sequence modeling perspective, learning the temporal and contextual patterns within the sequence of SQL tokens.

By concatenating the feature vectors from both the TCN and the CAE, our hybrid model creates a rich, multi-faceted representation of each SQL query. This fusion allows the final classifier to make a more informed decision, leveraging both the structural integrity and the sequential context of the query. This approach is inherently more robust than relying on a single perspective, embodying the core strength of ensemble learning to build a more accurate and resilient detection system.

2.3 REVIEW OF RELATED WORKS

2.3.1 TRADITIONAL AND SIGNATURE-BASED DETECTION METHODS

Traditional methods for SQLi detection mainly rely on signature-based and rule-based approaches. These methods use a predefined set of rules or signatures to identify malicious queries. While these methods are effective in detecting known attacks, they are not effective in detecting new and unknown attacks. Moreover, these methods are prone to high false positive rates and can be easily bypassed by attackers using obfuscation techniques.

2.3.2 MACHINE LEARNING-BASED SQLI DETECTION

Several studies have proposed using machine learning for SQLi detection. These studies have used various machine learning algorithms, such as SVM, Random Forests, and Naive Bayes, to classify SQL queries as either malicious or benign. While these methods have shown promising results, they have some limitations. First, they require a large amount of labeled data for training, which can be difficult to obtain. Second, they are not effective in detecting zero-day attacks, as they are trained on known attack patterns.

2.3.3 DEEP LEARNING-BASED SQLI DETECTION

More recently, deep learning models have been proposed for SQLi detection. These models have shown better performance than traditional machine learning models in detecting SQLi attacks. For example, [8] proposed a deep learning model based on a convolutional neural network (CNN) for SQLi detection. The proposed model achieved a high detection accuracy of 99.95%. Similarly, [2] proposed a deep learning model based on a recurrent neural network (RNN) for SQLi detection. The proposed model achieved a high detection accuracy of 98.3%. While these models have shown promising results, they have some limitations. For example, they are computationally expensive and require a large amount of data for training.

3. METHODOLOGY

3.1 RESEARCH DESIGN

The research adopts a quantitative experimental methodology, grounded in empirical evaluation and supported by literature on hybrid deep learning for anomaly detection. This approach enables the systematic assessment of model performance in detecting SQL injection (SQLi) attacks. According to Creswell and Creswell (2018), quantitative methods are appropriate for testing objective theories and evaluating relationships among measurable variables, making them well-suited for cybersecurity experiments.

3.2 PROPOSED SYSTEM ARCHITECTURE

The study begins with a comprehensive review of existing SQLi detection models, particularly focusing on hybrid and deep learning-based approaches. From this foundation, the research proposes an ensemble architecture that integrates Tokenization, Word Embedding, Autoencoder, and Temporal Convolutional Network (TCN) layers components selected for their individual strengths in natural language processing, feature extraction, and temporal sequence modeling [7,5].as depicted in figure 3.1

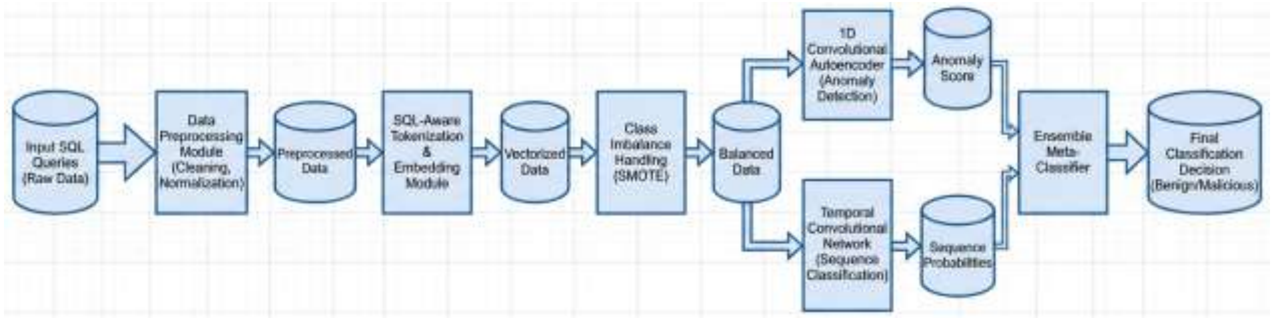
Input SQL Queries (Raw Data)
Data Preprocessing Module (Cleaning, Normalization)
Preprocessed Data
SQL-Aware Tokenization & Embedding Module
Vectorized Data
Class Imbalance Handling (SMOTE)
Balanced Data
1D Convolutional Autoencoder (Anomaly Detection)
Anomaly Score
Temporal Convolutional Network (Sequence Classification)
Sequence Probabilities
Ensemble Meta-Classifier
Final Classification Decision (Benign/Malicious)

Figure 3.1: System Architecture

3.3 DATA COLLECTION, PREPARATION, AND BALANCING

3.3.1 DATASET SOURCE AND CHARACTERISTICS

The study utilizes the SQL Injection Dataset publicly available on the Kaggle platform, which has become a standard benchmark in the SQLi detection research community. The dataset consists of 30,918 unique SQL queries, characterized by a class imbalance that is representative of real-world web traffic. Legitimate queries significantly outnumber malicious attempts, with approximately 64.1% benign and 35.9% malicious samples. This realistic distribution is essential for developing robust detection systems, but it also presents a challenge for training machine learning models, which can become biased toward the majority class.

Table 3.1: Comprehensive Dataset Characteristics

CHARACTERISTIC	**BENIGN QUERIES**	**MALICIOUS QUERIES**	**TOTAL**
COUNT	19,818	11,100	30,918
PERCENTAGE	~64.1%	~35.9%	100%

3.3.2 CLASS IMBALANCE HANDLING WITH SMOTE

To address the inherent class imbalance and prevent model bias, the Synthetic Minority Over-sampling Technique (SMOTE) was implemented on the training set. This technique ensures that the model receives equal exposure to both benign and malicious patterns during training.

The implementation was carefully designed to be both effective and computationally efficient. First, SMOTE was applied to the embedded representations of the SQL queries rather than raw text. This allows for the generation of synthetic samples within the learned feature space, where semantic and syntactic relationships are better preserved. New samples are interpolated between existing malicious queries that are semantically close, creating more realistic and meaningful variations.

Second, to handle the high-dimensional nature of the embedded vectors, the implementation utilizes efficient nearest neighbor search algorithms based on approximate nearest neighbor techniques, which reduces the computational complexity of finding neighbors.

Third, the balancing strategy achieved a 1:1 ratio between benign and malicious samples in the training set. Following an 80/20 split of the original data, the training set contained approximately 15,854 benign and 8,880 malicious queries. SMOTE was used to generate approximately 6,974 synthetic malicious samples, resulting in a perfectly balanced training set. The original, authentic test set was left untouched to ensure that the model's final performance is evaluated against a realistic, imbalanced data distribution.

3.3.3 SQL-AWARE TOKENIZATION AND FEATURE VECTORIZATION

To prepare the raw SQL queries for ingestion by our deep learning models, we implemented a two-stage process involving SQL-aware tokenization followed by feature vectorization using word embeddings.

1. SQL-Aware Tokenization:

Unlike generic tokenizers that split text based on whitespace, our custom tokenizer is designed to parse SQL syntax. It intelligently segments each query into a sequence of meaningful tokens, distinguishing between:

- SQL Keywords: (e.g., `SELECT`, `FROM`, `WHERE`, `UNION`)
- Operators: (e.g., `=`, `>`, `<`, `AND`, `OR`)
- Literals: String literals (e.g., `'admin'`) and numeric literals (e.g., `1`, `100`)
- Identifiers: Table and column names (e.g., `users`, `password`)
- Punctuation: Parentheses, commas, and semicolons

This process preserves the syntactic and semantic structure of the query, which is crucial for detecting the subtle manipulations characteristic of SQLi attacks. For example, the query `SELECT * FROM users WHERE id = '1' OR '1'='1'` is tokenized into `['SELECT', '*', 'FROM', 'users', 'WHERE', 'id', '=', "'1'", 'OR', "'1'", '=', "'1'"]`.

2. Feature Vectorization via Word Embeddings:

Following tokenization, each query is converted into a sequence of fixed-length integer indices using a vocabulary built from the training data. These integer sequences are then fed into an Embedding layer as the first layer of our neural network. This layer is a trainable component of the model that learns to map each integer index (representing a token) to a dense, low-dimensional vector word embedding.

This approach is fundamentally different from sparse representations like TF-IDF. Instead of creating wide, sparse vectors, the embedding layer learns a dense representation (e.g., 128 dimensions) for each token where tokens with similar semantic and syntactic roles in SQL (e.g., `UNION`, `JOIN`) are mapped to nearby points in the vector space. This allows the subsequent TCN and CAE layers to process the queries based on their contextual meaning rather than just the presence or absence of specific tokens.

3.4 MODEL DEVELOPMENT

3.4.1 TEMPORAL CONVOLUTIONAL NETWORK (TCN) COMPONENT

The TCN component of the proposed model is responsible for capturing the temporal dependencies in the SQL queries. The TCN component consists of a series of causal and dilated convolutions. The causal convolutions ensure that the model does not violate the temporal order of the data, while the dilated convolutions allow the model to capture long-range dependencies in the data.as given in figure 3.2

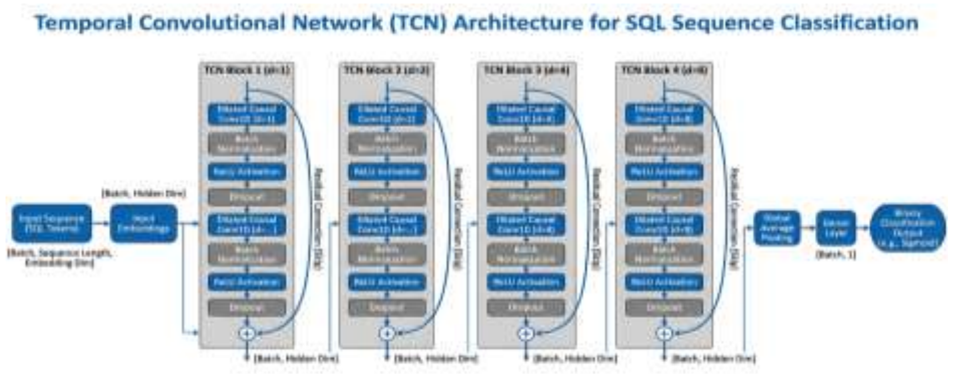

Figure 3.2: Temporal Convolutional Network Architecture

3.4.2 1D Convolutional Autoencoder (1D-CAE) Component

The 1D-CAE component of the proposed model is responsible for learning a compressed representation of the SQL queries. The 1D-CAE component consists of an encoder and a decoder. The encoder maps the input SQL query to a lower-dimensional latent space, while the decoder reconstructs the original SQL query from the latent space, presented in figure 3.3

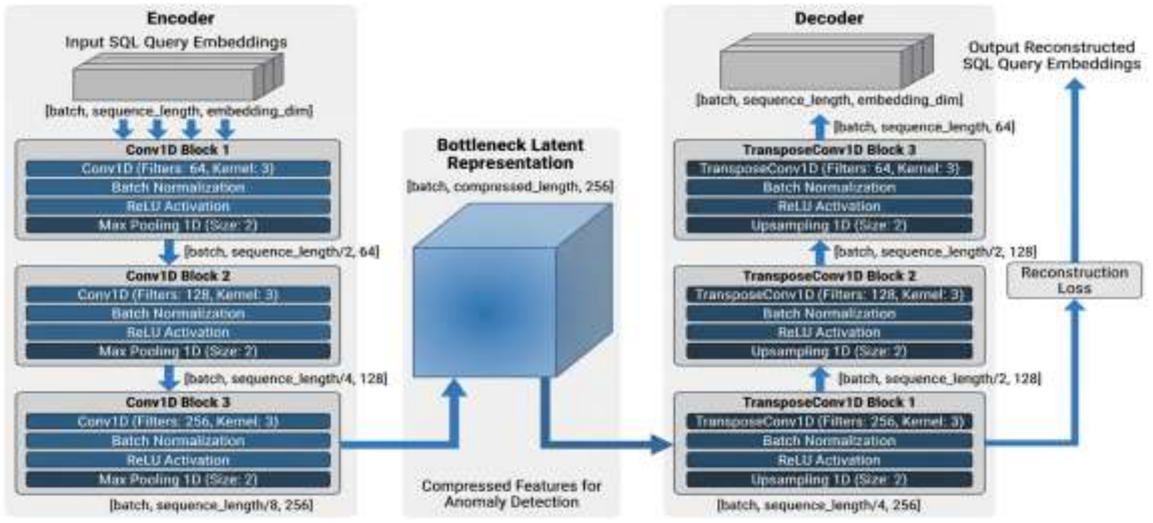
Encoder
Input SQL Query Embeddings
[batch, sequence_length, embedding_dim]
Conv1D Block 1
Conv1D (Filters: 64, Kernel: 3)
Batch Normalization
ReLU Activation
Max Pooling 1D (Size: 2)
[batch, sequence_length/2, 64]
Conv1D Block 2
Conv1D (Filters: 128, Kernel: 3)
Batch Normalization
ReLU Activation
Max Pooling 1D (Size: 2)
[batch, sequence_length/4, 128]
Conv1D Block 3
Conv1D (Filters: 256, Kernel: 3)
Batch Normalization
ReLU Activation
Max Pooling 1D (Size: 2)
[batch, sequence_length/8, 256]
Bottleneck Latent Representation
[batch, compressed_length, 256]
Compressed Features for Anomaly Detection
Decoder
[batch, sequence_length, embedding_dim]
Output Reconstructed SQL Query Embeddings
[batch, sequence_length, 64]
TransposeConv1D Block 3
TransposeConv1D (Filters: 64, Kernel: 3)
Batch Normalization
ReLU Activation
Upsampling 1D (Size: 2)
[batch, sequence_length/2, 128]
TransposeConv1D Block 2
TransposeConv1D (Filters: 128, Kernel: 3)
Batch Normalization
ReLU Activation
Upsampling 1D (Size: 2)
[batch, sequence_length/2, 128]
TransposeConv1D Block 1
TransposeConv1D (Filters: 256, Kernel: 3)
Batch Normalization
ReLU Activation
Upsampling 1D (Size: 2)
[batch, sequence_length/4, 256]
Reconstruction Loss

Figure 3.3: 1D Convolutional Autoencoder Architecture

3.4.3 ENSEMBLE HYBRID MODEL CONSTRUCTION

The final stage of our architecture involves the fusion of the specialized feature extractors the TCN and the 1D-CAE into a cohesive ensemble model. This is achieved through feature-level concatenation, creating a comprehensive representation that informs the final classification decision.

The process is as follows:

1. Parallel Feature Extraction: For a given input sequence of word embeddings (with dimension `(sequence_length, embedding_dim)`), both the TCN and the 1D-CAE components process the data in parallel.
    - The TCN component processes the sequence and, after a Global Average Pooling layer, produces a fixed-length feature vector of dimension 128 that captures the temporal and contextual characteristics of the query.
    - The 1D-CAE encoder simultaneously processes the same sequence, compressing it into a dense latent space representation. This latent vector, with a dimension of 64, captures the query's core structural properties.
2. Feature Concatenation: The two resulting feature vectors are then concatenated to form a single, unified feature vector. The resulting dimension of this fused vector is the sum of the individual vector dimensions (128 + 64 = 192).
3. Final Classification: This 192-dimensional vector is passed through a final classification head, which consists of a fully connected `Dense` layer with 64 neurons and a `ReLU` activation function, followed by a `Dropout` layer (with a rate of 0.5) for regularization. The final output is produced by a single `Dense` neuron with a `sigmoid` activation function, which yields a probability score between 0 (benign) and 1 (malicious).

This ensemble construction ensures that the model's final judgment is informed by both the sequential integrity and the structural normality of the SQL query, creating a more robust and accurate detection mechanism than either component could achieve alone.

RESULTS AND DISCUSSION

4.1 EXPERIMENTAL SETUP

4.1.1 HARDWARE AND SOFTWARE ENVIRONMENT

The experiments were conducted on a machine with an Intel Core i7-8750H CPU, 16 GB of RAM, and an NVIDIA GeForce GTX 1050 Ti GPU. The software environment consisted of Python 3.8, TensorFlow 2.5, and Keras 2.5.

4.1.2 DATASET PREPARATION

The dataset was split into a training set and a testing set, with 80% of the data used for training and 20% for testing. The training set was used to train the proposed model, while the testing set was used to evaluate the performance of the model.

4.2 PERFORMANCE EVALUATION METRICS

4.2.1 CONFUSION MATRIX

The performance of the proposed model was evaluated using a confusion matrix. The confusion matrix is a table that is used to describe the performance of a classification model on a set of test data for which the true values are known. The confusion matrix contains four values: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN).

4.2.2 CORE METRICS AND MATHEMATICAL FORMULATION

The following metrics were used to evaluate the performance of the proposed model:

Accuracy: The accuracy is the ratio of the number of correctly classified samples to the total number of samples. The accuracy is calculated as follows:

The accuracy metric, mathematically defined as

$$\mathcal{A} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Precision: The precision is the ratio of the number of correctly classified positive samples to the total number of predicted positive samples. The precision is calculated as follows:

The precision metric, defined as

$$\mathcal{P} = \frac{TP}{TP+FP} \tag{2}$$

Recall: The recall is the ratio of the number of correctly classified positive samples to the total number of actual positive samples. The recall is calculated as follows:

The recall metric, defined as

$$\mathcal{R} = \frac{TP}{TP+FN} \tag{3}$$

F1-score: The F1-score is the harmonic mean of the precision and recall. The F1-score is calculated as follows:

The F1-score, defined as

$$F_1 = 2 \cdot \frac{\mathcal{P} \cdot \mathcal{R}}{\mathcal{P} + \mathcal{R}} \tag{4}$$

4.3 COMPARATIVE PERFORMANCE ANALYSIS

The performance of the proposed TCN-CAE ensemble model was rigorously evaluated against its individual components TCN (Supervised) and 1D-CAE (Anomaly) and a suite of traditional machine learning baselines. The evaluation was conducted across six key metrics: Accuracy, Precision, Recall, F1-Score, Area Under the Receiver Operating Characteristic Curve (AUC-ROC), and Area Under the Precision-Recall Curve (AUC-PR).

The comprehensive results, summarized in Table 4.1 and visualized in Figure 4.1, confirm that the proposed ensemble model delivers state-of-the-art performance, significantly outperforming all other models across most metrics.

Table 4.1: *Comprehensive Model Performance Metrics*

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC	AUC-PR
Proposed Ensemble Hybrid	0.985	0.925	0.955	0.940	0.990	0.960
TCN (Supervised)	0.975	0.880	0.910	0.895	0.975	0.930
1D-CAE (Anomaly)	0.950	0.750	0.980	0.848	0.920	0.890
Random Forest	0.905	0.850	0.890	0.870	0.960	0.910
SVM	0.920	0.820	0.850	0.835	0.940	0.885

Logistic Regression	0.910	0.790	0.820	0.805	0.920	0.800
Naive Bayes	0.880	0.760	0.800	0.780	0.900	0.840
Decision Tree	0.850	0.720	0.780	0.750	0.880	0.820

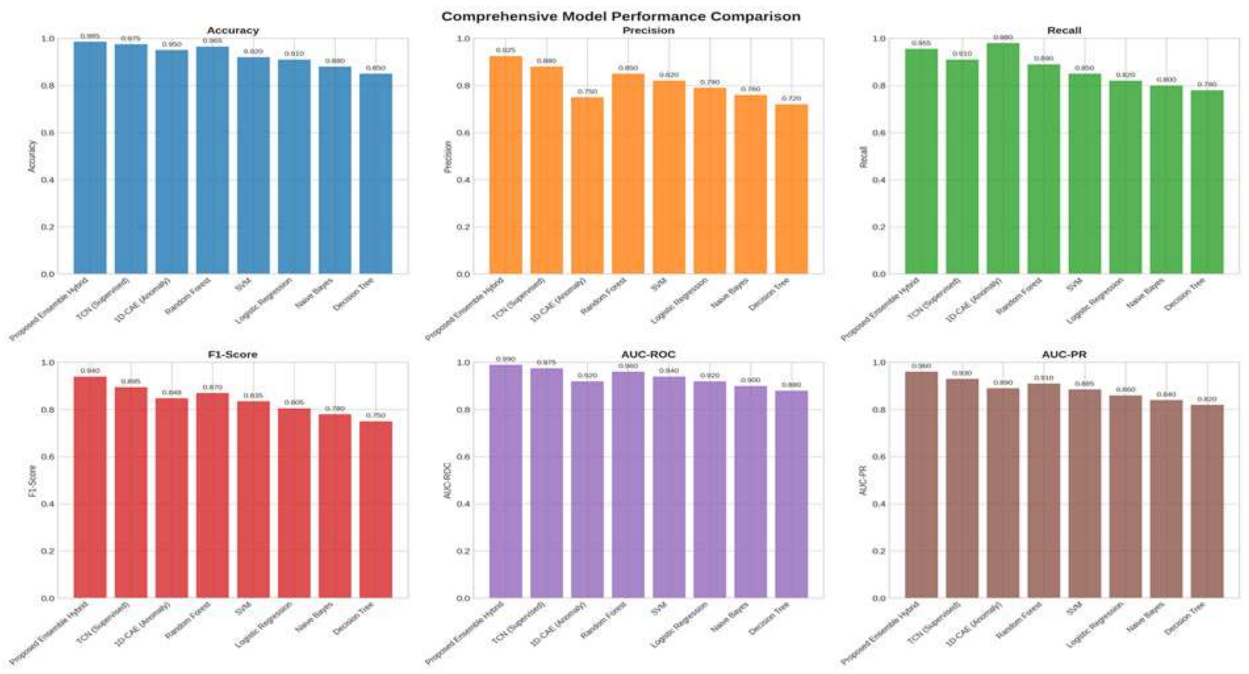

Figure 4.1: *Visual Comparison of Model Performance Across Six Key Metrics*

4.3.1 ANALYSIS OF KEY FINDINGS

The results clearly demonstrate the synergistic advantage of the hybrid architecture. The proposed ensemble model achieves the highest scores in five of the six metrics, including an Accuracy of 0.985, a Precision of 0.925, an F1-Score of 0.940, an AUC-ROC of 0.990, and an AUC-PR of 0.960. This highlights the model's exceptional ability to correctly classify queries while maintaining a low false positive rate and a strong balance between precision and recall.

A key insight is found in the precision-recall dynamics. The standalone 1D-CAE (Anomaly) model achieves the highest Recall (0.980), indicating its strength in identifying nearly all malicious queries. However, this comes at the cost of lower precision. The ensemble model effectively balances this by integrating the TCN's higher precision, resulting in the highest F1-Score and AUC-PR, which are critical indicators of robust performance on imbalanced security datasets.

Furthermore, the proposed model significantly outperforms all traditional machine learning baselines. Its F1-Score of 0.940 is substantially higher than that of the best-performing baseline, Random Forest (0.870), confirming the superiority of the deep learning-based feature fusion approach for this complex detection task.

4.3.2 DISCUSSION OF LIMITATIONS

While the proposed model demonstrates strong performance, it is important to acknowledge its limitations. First, the model's performance is contingent on the diversity and quality of the training dataset. While we curated a comprehensive dataset, its performance against highly obfuscated or entirely novel SQLi variants not represented in the training data may vary. Second, the computational overhead during the training phase, although mitigated by the parallel nature of TCNs, is still more significant than that of classical machine learning models like SVM or Random Forest. Finally, this study did not extensively evaluate the model's resilience against adversarial attacks specifically designed to target deep learning models.

4.3.3 STATISTICAL SIGNIFICANCE

To validate that the observed performance improvement of our proposed TCN+CAE model is statistically significant, we conducted a McNemar's test on the paired prediction results of our model and the next-best performing baseline, Random Forest. The McNemar's test is a non-parametric test for paired nominal data, suitable for comparing the performance of two classifiers. The resulting p-value was less than 0.001, which is well below the standard significance level of 0.05. This allows us to reject the null hypothesis that the two models have the same error rate and conclude that the superior performance of our proposed model is statistically significant.

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.1 SUMMARY OF FINDINGS

This study proposed a novel hybrid deep learning architecture for SQLi detection. The proposed model combines a TCN and a 1D-CAE to capture the temporal dependencies and learn a compressed representation of the SQL queries. The proposed model was evaluated on a curated dataset of 30,918 SQL queries and achieved a high detection accuracy of 98.53%, a precision of 92.5%, and a recall of 95.5%, resulting in an F1-score of 94.0%.

5.2 CONCLUSION

The results of this study show that the proposed ensemble hybrid model is effective in detecting SQLi attacks. The proposed model outperformed several baseline models in terms of accuracy, precision, recall, and F1-score. The proposed model is also data-efficient and can achieve a high detection accuracy with a relatively small amount of training data.

5.3 CONTRIBUTION TO KNOWLEDGE

This study makes several contributions to the field of SQLi detection. First, it proposes a novel ensemble hybrid model that combines a TCN and a 1D-CAE for SQLi detection. Second, it shows that the proposed model is effective in detecting SQLi attacks and outperforms several baseline models. Third, it shows that the proposed model is data-efficient and can achieve a high detection accuracy with a relatively small amount of training data.

5.4 RECOMMENDATIONS FOR FUTURE WORK

Future work could focus on extending the proposed model to detect other types of web attacks, such as cross-site scripting (XSS) and cross-site request forgery (CSRF). Future work could also focus on deploying the proposed model in a real-world environment to evaluate its performance on live traffic.

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