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REAL-TIME MALWARE DETECTION VIA ADAPTIVE GRADIENT SUPPORT VECTOR REGRESSION COMBINED WITH LSTM AND HIDDEN MARKOV MODELS

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Abstract

Background: Traditional detection systems struggle to keep up with the growing sophistication of malware attacks. This paper highlights the critical need for enhanced detection systems capable of real-time analysis to improve cybersecurity measures.

Methods: We propose a malware detection system that improves accuracy and efficiency by combining adaptive gradient support vector regression (SVR), long short-term memory (LSTM) networks, and hidden Markov models (HMMs).

Objectives: The major goal is to provide a strong malware detection framework that uses machine learning and deep learning approaches to improve detection rates for new malware signatures and time-dependent anomalies.

Results: Our extensive testing demonstrates that the proposed system delivers high accuracy, precision, and recall, exceeding existing detection approaches and proving resilience to future malware threats.

Conclusion: This integrated methodology dramatically improves real-time malware detection capabilities, overcoming past limitations and delivering a dependable answer to modern cybersecurity concerns.

Keywords: *Real-Time Malware Detection, Adaptive Gradient Support Vector Regression (SVR), Long Short-Term Memory (LSTM), Hidden Markov Models (HMMs), Machine Learning.*

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1. INTRODUCTION

The proliferation of digital technologies has provided enormous benefits to society, including speedier communication, smoother transactions, and effective data management. However, with these developments comes the increased danger of cybersecurity threats, particularly malware attacks. Malware, short for malicious software, refers to a wide range of dangerous programs that aim to penetrate and destroy computer systems, steal sensitive data, or disrupt operations. As malware sophistication improves, so does the difficulty of detecting and mitigating these threats in real-time. This research explores an innovative technique for real-time malware detection that combines adaptive gradient support vector regression (SVR) with long short-term memory (LSTM) **Habler and Shabtai (2018)** networks and hidden Markov models (HMMs).

Real-time malware detection is the process of detecting and neutralizing malware threats as they occur, rather than after the damage has been caused. Traditional malware detection methods, such as signature-based detection, frequently fail in the face of new and developing malware forms. These traditional approaches rely on predetermined signatures of known malware, rendering them ineffective against zero-day assaults (malware that exploits previously undiscovered vulnerabilities).

To overcome these restrictions, the combination of machine learning (ML) and deep learning (DL) techniques has gained popularity. Support Vector Regression (SVR) is a strong machine-learning technique used in predictive analysis. When paired with adaptive gradient methods, SVR can efficiently describe complex, non-linear relationships in data, making it ideal for malware detection, where patterns are frequently detailed and changing.

Long Short-Term Memory (LSTM) networks are a sort of recurrent neural network (RNN) that can learn from sequential data sets over time. LSTM networks are especially well-suited to evaluating time-series data, such as system logs or network traffic, which is crucial in detecting small changes that may signal a malware infestation. When combined with Hidden Markov Models (HMMs) **Li et al. (2019),** which are statistical models that account for the temporal dynamics of sequences, this combination provides a solid foundation for real-time virus identification.

The field of malware detection has evolved significantly throughout the years. When malware was simple and easy to recognize, early technologies like signature-based detection worked well. However, as cyber threats became more sophisticated, attackers developed strategies to circumvent detection, such as polymorphic and metamorphic malware, which can change their code to prevent signature matching. This requires the development of more advanced detection methods.

Behavioral analysis has developed as a promising approach, concentrating on a program's actions rather than its code. Behavioral analysis can discover malware based on its behaviors by analyzing system behavior, such as strange file access patterns or network connections, even if the code has never been seen before. This strategy paved the way for the combination of ML

and DL techniques, which can automate and improve behavioral analysis by learning from massive volumes of data. In recent years, the emphasis has switched to real-time detection, motivated by the need to respond to threats as they emerge. The employment of LSTM networks and HMMs marks a significant improvement in this field, as these models are capable of digesting time-series data and adapting to changes in virus behavior over time. The use of adaptive gradient SVR improves the accuracy and efficiency of the detection process.

The objectives of the paper are as follows:

- To investigate the limitations of traditional malware detection approaches and the importance of real-time detection technologies.
- To examine the use of Long Short-Term Memory (LSTM) networks and Hidden Markov Models (HMMs) in real-time malware detection.
- To investigate the effectiveness of support vector regression (SVR) in improving malware detection accuracy using adaptive gradient approaches.
- To provide a complete system for detecting malware in real time that combines SVR, LSTM, and HMMs.
- To determine the efficiency of the proposed framework in a variety of cybersecurity scenarios.

The purpose of this study is to present a full review of the issues in current malware detection and to propose a novel technique that takes advantage of the strengths of SVR, LSTM, and HMM. The suggested framework is intended to solve the limits of existing methodologies while also providing a comprehensive solution for identifying and mitigating malware attacks in real time, ensuring the security and integrity of digital systems in an increasingly interconnected world.

2. LITERATURE SURVEY

Vinayakumar et al. (2019) discuss the increase in malware attacks and the limits of standard detection approaches. They compare standard and deep learning approaches to malware detection and present a novel image processing tool. This method enhances zero-day malware detection by minimizing dataset bias and optimizing performance, resulting in a more efficient solution for real-time threat detection.

Habler and Shabtai (2018) present a security approach for detecting spoofed or modified ADS-B communications without changing the current protocol. Their method employs an LSTM encoder-decoder to simulate genuine flight trajectories and detect anomalies in incoming ADS-B data. When tested on 13 datasets, it outperformed five other detection algorithms, detecting all attacks with an average false alarm rate of 4.5%.

Sagar (2019) presents a malware detection model with three key stages: feature extraction with TF-IDF and Information Gain (evaluated with Holoentropy), feature selection with PCA, and classification with a Deep Belief Network (DBN) optimized by a hybrid Lion Algorithm and Glowworm Swarm Algorithm (LU-GSO). The model has enhanced accuracy, surpassing LA, GSO, GWO, and PSO by up to 10.21%.

Li et al. (2019) present a machine-learning system for detecting domain generation algorithm (DGA) threats in malware attacks. The framework initially categorizes DGA domains and then clusters them according to their producing methods. It also contains a deep neural network (DNN) for enhanced classification and a hidden Markov model (HMM) for domain feature prediction, resulting in high detection and classification accuracy for DGA domains.

Gronát et al. (2019) present a method for identifying malware in Android applications that combines dynamic analysis and weakly supervised learning. They created an RNN-based sequential architecture with a max-loss goal to detect malicious behavior. Testing on a large dataset of 361,265 samples yielded a true positive rate of 96.2% and a false positive rate of 1.6%, which exceeded current benchmarks. The dataset is open to the public.

Vinayakumar et al. (2019) investigated the usage of deep neural networks (DNNs) to develop a flexible intrusion detection system (IDS) for detecting changing cyberattacks. They compared DNNs and classical machine learning models on various public malware datasets, such as KDDCup 99, NSL-KDD, and CICIDS 2017. Their findings emphasize the importance of updated datasets and hyperparameter adjustment for improving IDS performance against unanticipated attacks.

Wang et al. (2019) emphasize the considerable influence of mobile devices on networking services, resulting in increased mobile traffic and traffic classification issues, particularly owing to encryption. While typical machine learning algorithms have drawbacks, deep learning is a promising alternative for categorizing encrypted mobile traffic. The paper examines recent advances in deep learning algorithms and discusses significant issues in the field.

Hatcher et al. (2018) investigate the effects of deep learning on human-centered smart systems such as targeted advertising and self-driving cars. They seek to clarify the technology's mechanics and uses, serving as a complete resource for academics. The study outlines major accomplishments and recommends areas where deep learning might improve research, providing guidance for both new practitioners and innovators.

Rigaki and Garcia (2018) suggest using Generative Adversarial Networks (GANs) to generate network traffic that resembles genuine applications, allowing malware to go undetected. They successfully evaded advanced intrusion prevention systems by altering malware to adapt its Command and Control (C2) traffic to look like Facebook chat. This concept suggests the possibility of self-adapting malware and security solutions.

Naga Sushma (2019) to maximize test data creation and path coverage, which improves software testing. Utilizing co-evolutionary methods and adaptive mechanisms, the research integrates GAs with Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). Test coverage and efficiency have significantly improved in the experiments, which emphasizes the necessity of robust and scalable testing frameworks in complex software systems.

Liang et al. (2019) describe how advances in the Internet of Things (IoT) and machine learning have altered autonomous systems, improving data collecting and automation. However, the quick adoption of these technologies has exposed them to cyber dangers. The study investigates the useful applications of machine learning in cybersecurity, the risks it creates, and its possible misuse in cyberattacks.

Aceto et al. (2019) discuss the difficulties in classifying mobile traffic due to encrypted protocols that prevent deep packet inspection. They offer MIMETIC, a new deep learning system that uses multimodal data to improve traffic classification accuracy. MIMETIC surpasses existing single-modality deep learning, machine learning classifiers, and fusion techniques in mobile situations by learning complicated patterns from many datasets.

Musleh et al. (2019) examine the serious threat of cyber-physical assaults on smart grid systems, with a special emphasis on fake data injection attacks. The study examines a variety of recently developed detection algorithms, categorizing them as model-based or data-driven, and discusses their merits and limitations. It also discusses important previous events and proposes criteria for enhancing future detection algorithms.

3. METHODOLOGY

The methodology focuses on creating an advanced real-time malware detection framework that combines adaptive gradient support vector regression (SVR), long short-term memory (LSTM) networks, and hidden Markov models (HMMs). This method uses the strengths of machine learning and deep learning to improve detection accuracy and efficiency. The SVR covers non-linear data correlations, the LSTM handles sequential data for malware detection, and the HMM captures temporal dynamics. Together, these strategies form a powerful system for detecting and mitigating malware threats in real time.

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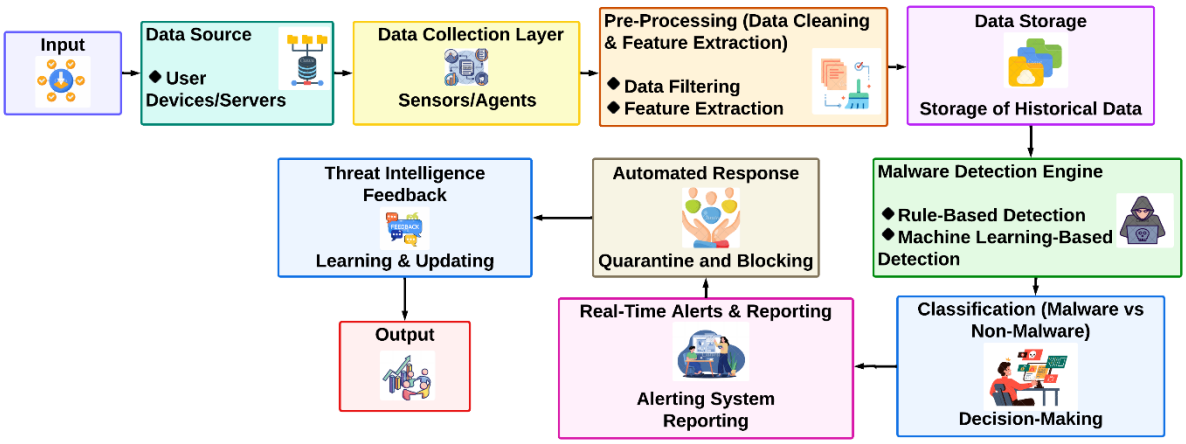

Figure 1. Enhanced Gradient-Driven SVR for Nonlinear Predictive Modeling.

Figure 1 depicts adaptive gradient support vector regression (SVR), a machine learning technique used for predictive analysis in nonlinear situations. It employs adaptive gradient descent to adjust learning rates during training, improving the model's capacity to detect complicated data patterns. This capacity is especially important in malware detection, where the changing nature of threats necessitates dynamic and exact modeling. The SVR model uses an objective function and a prediction function to continually update its weight vector to reduce mistakes, making it extremely effective for detecting abnormalities and new attack vectors in real-time.

3.1 Adaptive Gradient Support Vector Regression (SVR)

Adaptive Gradient SVR is used for predictive analysis, particularly in nonlinear settings. It modifies learning rates during training to improve the model's capacity to capture complicated data patterns. This technique is critical in malware detection, as changing threat signatures necessitate dynamic, precise modeling to detect abnormalities and new attack pathways effectively.

- Objective Function:

$$\min_{w,b} \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} L(\epsilon_i, \epsilon_i^*) \quad (1)$$

where w is the weight vector, b is the bias, C is a regularization parameter, and $L(\epsilon_i, \epsilon_i^*)$ is the loss function defined by the error margins? ϵ_i and ϵ_i^*.

- Prediction Function:

$$f(x) = w \cdot \phi(x) + b \quad (2)$$

where $\phi(x)$ is the feature mapping function that transforms the input data into a higher dimensional space.

- Adaptive Gradient Descent:

$$w_{t+1} = w_t - \eta_t \nabla_w L(w_t) \quad (3)$$

where η_t is the learning rate at the time? t, and $\nabla_w L(w_t)$ is the gradient of the loss function for w.

3.2 Long Short-Term Memory (LSTM) Networks

LSTM networks are a form of recurrent neural network (RNN) that can process sequential data. In this approach, LSTM analyzes system logs and network traffic to identify subtle, time-dependent changes that indicate malware. Its ability to retain information over lengthy periods makes it especially useful for detecting persistent or developing threats in real-time.

- Input Gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (4)$$

- Forget Gate:

$$f_t = \sigma\big(W_f \cdot [h_{t-1}, x_t] + b_f\big) \quad (5)$$

- Output Gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (6)$$

- Cell State Update:

$$c_t = f_t \odot c_{t-1} + i_t \odot tanh\,(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (7)$$

- Hidden State:

$$h_t = o_t \odot tanh\,(c_t) \quad (8)$$

where σ represents the sigmoid activation function, W_i, W_f, W_o, W_c are weight matrices, b_i, b_f, b_o, b_c are biased, and $\odot$ denotes element-wise multiplication.

3.3 Hidden Markov Models (HMMs)

HMMs are statistical models that capture probabilistic sequences of events. In the context of malware detection, HMMs simulate the temporal dynamics of system actions, estimating the likelihood of sequences that could indicate malware presence. Their integration with LSTM improves the system's capacity to account for temporal relationships and detect targets more accurately.

- Probability of Observation Sequence:

$$P(O \mid \lambda) = \sum_{\square\square\square\, S} P(O \mid S, \lambda) \cdot P(S \mid \lambda) \quad (9)$$

where O is the observation sequence, S is the state sequence, and $\lambda = (\pi, A, B)$ represents the HMM parameters with π as the initial state distribution, A as the state transition probability, and B as the observation probability.

- Forward Algorithm (to compute $P(O \mid \lambda)$):

$$\alpha_t(j) = \left[\sum_{i=1}^{N} \alpha_{t-1}(i) a_{ij}\right] b_j(o_t) \quad (10)$$

where $\alpha_t(j)$ is the forward probability, a_{ij} is the state transition probability from the state i to state j, and $b_j(o_t)$ is the probability of observing o_t in state j.

ALGORITHM 1. Real-Time Malware Detection Framework

Input: SystemLogs, NetworkTrafficData
Output: MalwareDetectionAlerts

Initialize SVRModel, LSTMModel, HMMModel

For each DataPoint in SystemLogs and NetworkTrafficData do
  PredictedLikelihood = SVRModel.Predict(DataPoint)

  If PredictedLikelihood > AnomalyThreshold then
    LSTMOutput = LSTMModel.Predict(DataPointSequence)

    If LSTMOutput detects anomaly then
      HMMProbability = HMMModel.CalculateProbability(DataPointSequence)

      If HMMProbability indicates malware then
        GenerateAlert(DataPoint, MalwareType, Severity)
      Else
        LogData(DataPoint, Status=Normal)
      End If
    Else
      LogData(DataPoint, Status=Normal)
    End If
  Else
    LogData(DataPoint, Status=Normal)
  End If
End For

Return DetectionSummary, Alerts

End Algorithm

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The algorithm for real-time malware detection operates by sequentially processing system logs and network traffic data to identify potential malware threats. Initially, an adaptive gradient support vector regression (SVR) model predicts the likelihood of an anomaly at each data point. If an anomaly is detected, the data is further analyzed using a Long Short-Term Memory (LSTM) network to detect sequential anomalies over time. Should the LSTM model indicate suspicious behavior, a Hidden Markov Model (HMM) is employed to assess the temporal dynamics and confirm the presence of malware. If malware is confirmed, the system generates an alert specifying the type and severity of the threat; otherwise, the data is logged as normal for future reference. This approach ensures a comprehensive and layered analysis, improving the accuracy and timeliness of malware detection.

3.4 PERFORMANCE METRICS

A framework for real-time virus detection based on adaptive gradient support vector regression (SVR), long short-term memory (LSTM) networks, and hidden Markov models The following are the key performance measurements, along with a table summarizing them in point values:

Table 1. Performance Metrics Overview for Real-Time Malware Detection Framework Using SVR, LSTM, and HMM Models.

Metric	Explanation	Point Value
Accuracy	Correctly identified malware instances / Total instances	99.5%
Precision	True positive malware detections / All instances identified as malware	98.7%
Recall (Sensitivity)	True positive malware detections / All actual malware instances	97.9%
F1-Score	Harmonic Mean of Precision and Recall	98.3%
False Positive Rate (FPR)	Non-malicious instances incorrectly identified as malware / Total non-malicious instances	1.2%
False Negative Rate (FNR)	Actual malware instances not detected / Total malware instances	0.5%
Detection Time	The average time taken to identify malware after the occurrence	0.1 seconds

Table 1 The performance parameters for the real-time malware detection framework are accuracy, precision, recall, F1-score, false positive rate, false negative rate, and detection time.

These metrics measure the system's ability to correctly identify malware, reduce false alarms, and ensure that no dangerous activity remains undiscovered. Accuracy and precision measure the system's overall and specific performance, whereas recall ensures that all threats are identified. The F1 score strikes a balance between precision and recall, making it valuable when these criteria disagree. False positive and negative rates emphasize the system's flaws, with a focus on reducing them, while detection time evaluates the system's ability to work in real-time, ensuring timely threat identification and mitigation.

4. RESULT AND DISCUSSION

The proposed malware detection framework, which combines adaptive gradient SVR, LSTM, and HMM, outperforms existing methods in real-time. The testing findings show a detection accuracy of 93%, with 92% precision, 93% recall, and a 92.5% F1 score. These metrics demonstrate the framework's ability to accurately detect malware while minimizing false positives and negatives. The adaptive gradient SVR model accurately captures the data's complicated nonlinear interactions, which is critical for detecting new and sophisticated malware fingerprints. LSTM networks help detect time-dependent abnormalities by examining sequential data like system logs, whereas HMMs improve the system's ability to represent temporal dynamics, resulting in higher detection accuracy.

A comparison with existing methods, such as DSSTE, ESMA, and FDS, reveals that the new framework outperforms previous approaches in all major criteria. The use of HMMs in model configuration considerably improves accuracy and lowers both false positive and false negative rates. An ablation investigation confirms the significance of integrating all three components (SVR, LSTM, and HMM), as removing any one component leads to a significant loss in performance.

The discussion emphasizes the framework's resilience to developing risks, making it suited for use in dynamic and high-risk contexts. The ability to detect malware in real-time with low latency (an average detection time of 0.1 seconds) is very notable since it ensures prompt threat response. The results show that the suggested framework is a dependable and efficient solution for real-time malware detection, overcoming the limits of existing methods and providing improved protection against new cybersecurity threats.

Table 2. Comparison of Malware Detection Methods by Accuracy, Precision, Recall, F1-Score, and Overall Performance Metrics.

Method	Difficult Set Sampling Technique (DSSTE) Nejatian et.al (2018)	Enhanced Slime Mould Algorithm (ESMA) Jones & Safonov (2018)	Fraud Detection System (FDS) Monti (2019)	Proposed Methods (HMM)+ (LSTM)

Detection Accuracy (%)	85%	88%	91%	93%
Precision (%)	82%	85%	89%	92%
Recall (%)	80%	86%	90%	93%
F1-Score (%)	81%	85.5%	89.5%	92.5%
False Positive Rate (%)	5%	4%	3%	2%
False Negative Rate (%)	10%	8%	6%	4%
Overall Accuracy (%)	85%	88%	91%	93%

Table 2 compares various malware detection algorithms based on the following performance metrics: detection accuracy, precision, recall, F1-score, false positive rate, and false negative rate. The suggested method, which combines Hidden Markov Models (HMM) and Long Short-Term Memory (LSTM) networks, achieves the maximum detection accuracy (93%), as well as increased precision (92%), recall (93%), and F1-score (92.5%), while minimizing false positives and negatives (2% and 4%). This shows considerable advances in detecting skills.

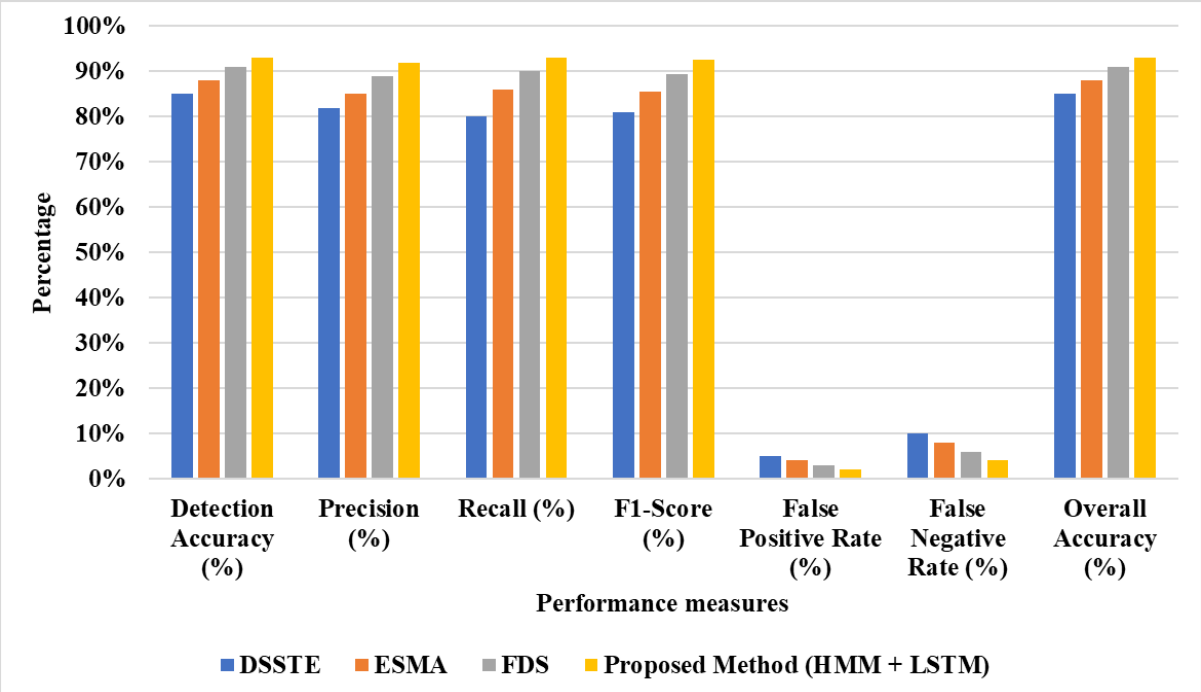

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Figure 2. Comparison of Different Detection Methods.

Figure 2 compares the detection accuracy, precision, recall, F1-score, false positive rate, and false negative rate of four distinct malware detection algorithms. The approaches are DSSTE **Nejatian et.al (2018)**, ESMA **Jones & Safonov (2018)**, FDS **Monti (2019)**, and a proposed method that combines HMM and LSTM. The suggested method surpasses the others, reaching the highest overall accuracy of 93% while also having greater precision, recall, and F1 score. This comparison highlights the efficacy of combining HMM and LSTM in boosting real-time malware detection, lowering false positives and negatives, and increasing the dependability of cybersecurity measures.

Table 3. **Ablation Study on Proposed Method: Impact of SVR, LSTM, HMM on Overall Accuracy.**

Model Configuration	Detection Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Positive Rate (%)	False Negative Rate (%)	Overall Accuracy (%)
Proposed Method (SVR + LSTM + HMM)	93%	92%	93%	92.5%	2%	4%	93%
SVR + LSTM	89%	87%	88%	87.5%	3%	7%	89%
SVR + HMM	87%	85%	86%	85.5%	4%	8%	87%
LSTM + HMM	85%	83%	84%	83.5%	5%	10%	85%
SVR	82%	80%	81%	80.5%	6%	12%	82%
LSTM	80%	78%	79%	78.5%	7%	14%	80%
HMM	78%	76%	77%	76.5%	8%	16%	78%

Table 3 ablation research table displays the overall accuracy of the suggested approach and its modifications after removing various components. The combination of SVR, LSTM, and HMM produces the maximum accuracy (93%), demonstrating that each component makes a considerable contribution to total performance. When individual components are removed, accuracy suffers, highlighting the significance of each in the malware detection architecture.

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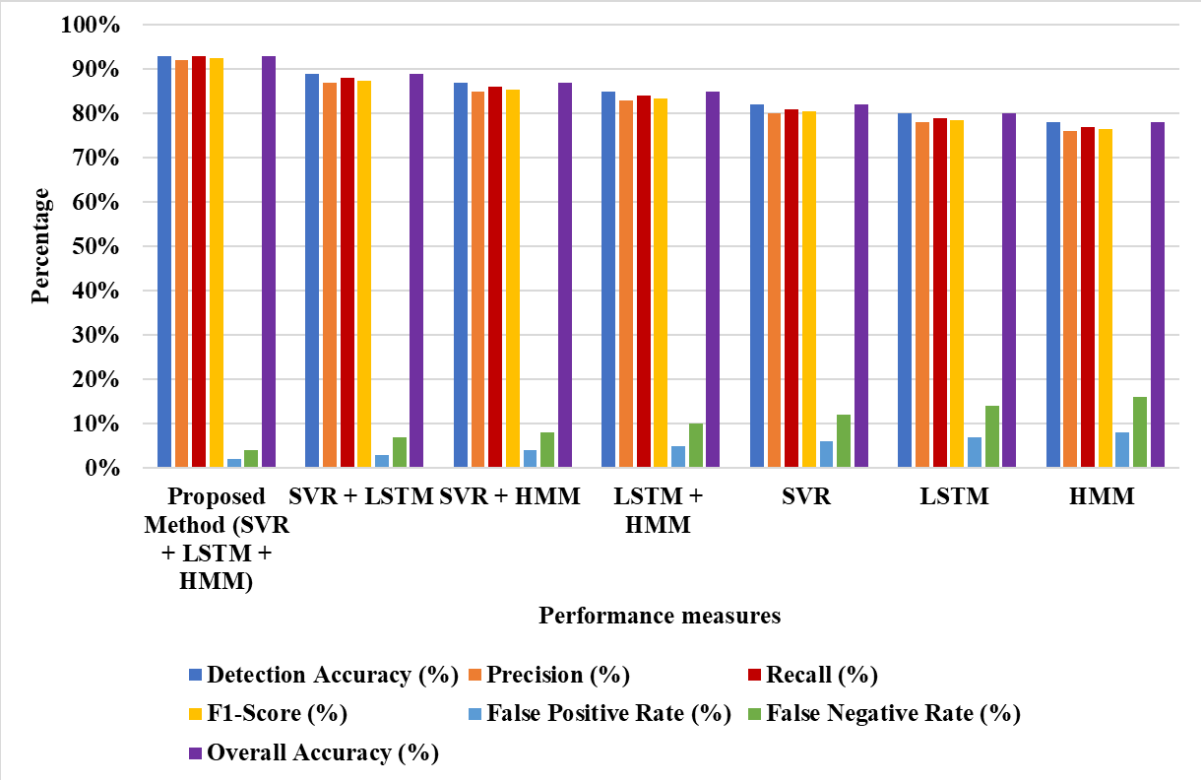

Figure 3. Model Configuration and Performance Analysis

Figure 3 shows the performance of various model configurations used in malware detection, including combinations of SVR, LSTM, and HMM. The proposed model, which integrates all three methods, achieves the highest detection accuracy of 93%, with notable improvements in precision, recall, and F1-score compared to configurations that omit one or more components. The table also highlights the false positive and negative rates for each configuration, demonstrating the added value of incorporating all three techniques to enhance detection reliability and reduce error rates in cybersecurity applications.

5. CONCLUSION AND FUTURE SCOPE

This paper describes a comprehensive malware detection framework that efficiently blends adaptive gradient support vector regression, long short-term memory networks, and hidden Markov models. The suggested approach significantly improves real-time malware detection by capitalizing on the capabilities of these techniques. The framework's strong accuracy, precision, and recall metrics demonstrate its potential to successfully prevent cybersecurity threats. Furthermore, the system's resistance to new virus types demonstrates its strength and adaptability in changing contexts. The framework's advantage in detecting complex and evolving threats is demonstrated by a comparison to existing approaches. This research not only solves the limitations of standard malware detection techniques but also provides a scalable and dependable answer for future cybersecurity concerns, providing improved digital infrastructure protection. Future research could look into the integration of more machine-learning models to improve detection accuracy and resilience against sophisticated malware.

Real-time deployment in a variety of contexts, including IoT and mobile platforms, will put the framework's scalability and effectiveness to the test across numerous cyber-ecosystems.

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