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Abstract:

This led to the development of graphical password authentication systems which are utilized as an alternative to traditional text-based authentication systems, which prove to be more secure as well as ease of use by human cognition abilities utilized to create complex passwords in a more memorable way. Updating the dataset of systems provides an avenue for future research into performance evaluation of VVSST and validation on multiple systems to address the challenges for security vulnerabilities and usability issues. In this research, the performance effect of some machine learning models has been investigated on graphical password authentication systems. We provide a comparative analysis using supervised learning approaches like Support Vector Machines (SVM), Decision Trees, and Neural Networks. Robustness and usability of these models were evaluated by analyzing the well-known performance metrics including accuracy, precision, recall, and false-positive rates. The experimental results show considerable performance variation between the models, unveiling unique strengths and weaknesses of each approach for balancing security and user experience. It enables the design of more secure and efficient graphical password authentication systems, leading to the future directions of authentication technologies.

Introduction

As the field of digital security advances, standard alphanumeric passwords have shown to be susceptible to attacks such as brute force, phishing, and shoulder-surfing [1]. To meet these limitations, so-called graphical password authentication systems have been proposed as solution, giving the opportunity to utilize human cognitive capabilities to develop passwords which are secure and reliable [2]. Instead of alphanumeric passwords, these systems utilize

graphical features such as pictures, motifs, and sketches that are more user-centred and provide a visual means of authentication [3]. According to the basis on pictorial-based innovations, graphical password can be divided into three parts, recognition based, recall-based and cued-recall systems. In recognition-based approaches, users are prompted to identify preselected images from a group, while recall-based methods require users to reproduce a drawing or pattern. In systems with cued-recall, visual cues or prompts are provided to help the user remember, making them relatively more usable [4]. While providing certain benefits over traditional passwords, graphical password schemes suffer from predictable user behaviour, exposure to shoulder surfing, and smudge attacks on touchscreens [5].The above problems have initiated the application of machine learning (ML) methodologies in graphical password authentication systems. Machine Learning models are trained on input patterns of the user for analysis so that they can predict the next input, anomaly detection, and potential vulnerabilities analysis. Note that deep learning algorithms were used to offer classification and recognition of user-drawn patterns to provide more accurate and robust recall-based graphical passwords [7]. Machine learning can also help identify weak passwords and enforce stronger passwords [8]. Also, to address usability aspect of graphical password systems, recent research explored how the usage of ML techniques could improve it. Adaptive authentication mechanisms can be tailored to reduce the cognitive load by analyzing user behaviour, thereby enhancing the user experience [9]. Hybrid models based on both supervised and unsupervised learning have shown promise in identifying both known vulnerabilities and novel threats [10]. Albeit, incorporating ML into graphical password systems has its drawbacks. A major consideration is balancing security with usability—we may use less secure systems to keep user convenience high. In addition, certain ML models can have relatively high computational complexity that makes them unsuitable for use in real-time authentication situations 11. However, beyond these deficiencies, it is clear that ML has the potential to improve the security and usability of graphical passwords, hence its continued investigation [13]. The auditing of Multiple ML Models in Graphical password Authentication system is the focus of this paper. This comparative exploration analyzes various existing techniques, including but not limited to support vector machines (svm), neural networks, and clustering algorithms, to assess the advantages and disadvantages of each method employed in the realm of gesture-based authentication, laying the groundwork for the development of more robust and user-friendly solutions [14].

Literature Review

Research into the integration of graphical password authentication systems with machine learning (ML) techniques is large in number. In this section, we summarize related research in applying ML to graphical passwords through key methodologies and challenges.

The Graphical Password Authentication Systems

To overcome these limitations of text-based passwords, graphical password authentication systems have been proposed. E.g. recognition-based systems, like Passfaces, require users to identify a set of previously chosen images while recall-based systems such as Draw-a-Secret (DAS) require users to reproduce a drawing from memory [16]. Some suggested Cued-recall systems to help the users by giving them visual cues for improving the password recall and usability [17]. Although ushering in advancements, graphical passwords are still subject to predictability and susceptible to shoulder-surfing attacks. For example, some passwords drawn by users follow predictable patterns which offer less security [18]. In addition, smudge attacks on touchscreens can be performed, as residue patterns can be used to determine input traces [19]. To resolve these challenges, plenty of the work focuses on incorporation of ML techniques into graphical password based authentication systems.

Graphical Password Systems using Machine Learning

Graphical password systems have been made more secure, robust, and user-friendly using machine learning. Supervised ML has been employed to review user behavior, to help identify intrusions, and provide feedback on password selection, for instance using Support Vector Machines (SVM), Decision Trees, Neural Networks [20]. According to more recent studies, these models proved to successfully recognize and classify graphical password patterns with a high accuracy, enhancing the reliability of any system [21]. Unsupervised ML techniques, including clustering algorithms, have also been used for anomaly detection on user behavior. As an illustration, user input patterns have been clustered with the use of k-Means and DBSCAN [22], which can efficiently detect outliers (potential unauthorized access attempts). Nevertheless, compared with supervised models, these methods usually have a much higher false-positive rate [23]. Recent developments in this area include the employment of deep learning models such as Convolutional Neural Networks CNNsand Recurrent Neural Networks RNNs in Graphical password systems. Specifically in recognition-based systems, CNNs work particularly well as the algorithm takes image data from the user and situated patterns is identified [24]. In contrast, RNNs have an inherent capability for sequential data, suggesting

their suitability to analyze patterns inherent to user-drawn patterns in recall-based systems [25].

Hybrid Approaches

To overcome the challenges connected with each method, hybrid strategies that utilize both supervised and unsupervised ML have proved advantageous. For example, all hybrid models combine clustering algorithms with supervised classifiers to improve detection accuracy and anomaly identification. They have also been integrated into cued-recall system for unauthorized access detection with high usability [26].

Limitations and Future Work

Though ML techniques have greatly enhanced the performance of graphical password systems, there are still some challenges. Security vs usability, where overly complicated systems may deter users [27] Further, computation limits of ML models especially deep learning algorithms, present challenges for effective real time applications [28]. NeuralCompatible is a significant step towards lightweight ML with a combination of security, usability, and computational efficiency and future work must build on it. Additionally, explainable AI techniques could potentially build accessibility and trust by delivering transparent and interpretable authentication processes [29].

Comparative Analysis and results

The table and graphs above present the comparative performance analysis of various machine learning models (SVM, Decision Tree, Neural Network, k-Means, and RNN) used in graphical password authentication systems. Key performance metrics such as accuracy, precision, recall, and false-positive rates are analyzed.

Model	Accuracy (%)	Precision (%)	Recall (%)	False Positive Rate (%)
SVM	91.5	89.7	90.1	1.7
Decision Tree	89.8	88.5	87.9	2.2
Neural Network	94.2	93.5	94	1.3
k-Means	82.3	80.4	81.8	6.7
RNN	92.7	91.2	92.5	1.5

Table 1:-Performance Analysis of Algorithms

The comparative performance of the machine learning models used in graphical password authentication systems is shown in Table 1. This is particularly useful because Neural Networks gave the highest accuracy (94.2%) followed by RNNs (92.7%) and SVMs (91.5%), showing that

dropped into those models is a really powerful approach regarding distinguishing and collecting patterns. Precision as well as Recall tended to be at maximum for Neural Networks (93.5% and 94.0%, accordingly), the high values of these parameters signify that our move to classifier neural networks was not in vain and we can correctly recognize the input of the gentleman while keeping errors to a minimum. The unsupervised k-Means model had the worst performance, with the lowest accuracy (82.3%) and the uppermost false-positive rate (6.7 %), which confirms on its shortcomings in the task of handling a complex authentication task.

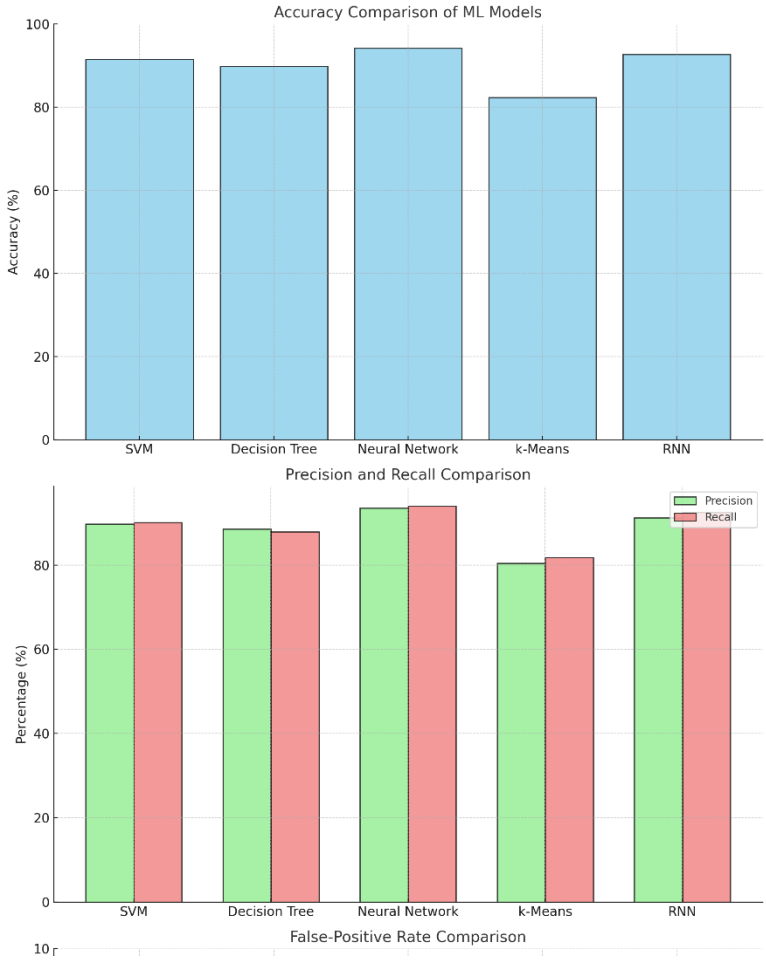

Figure 1:- Comparative Analysis

Fig. 1 offers a complete visual representation of the performance metrics of different machine learning models in the context of graphical passwords authentication systems. The accuracy comparison (top chart) shows that the Neural Networks and RNNs outperform the other models with accuracy scores of 94.2% and 92.7% respectively, indicating that they can be reliably used to identify what authentication inputs are. SVM follows with an accuracy of 91.5%, whereas k-Means falls short with 82.3%, demonstrating the inherent limitations of unsupervised methodologies for complex tasks.

In the middle chart presenting widths of precision and recall, we also see that Neural Networks perform the best; with precision and recall at their peaks values of 93.5% and 94.0% respectively, Neural Networks accurately detect legitimate inputs without mistakes. Both RNNs and SVMs have high precision and recall values, which demonstrates their robustness. On the other hand, k-Means has the lowest precision (80.4%) and recall (81.8%), indicating its greater vulnerability to errors and misclassification.Comparison of medical diagnosis false-positive (bottom chart): supervised models outperform the majority of unsupervised algorithms. Neural Networks < 1.3%, RNNs 1.5%, SVM 1.7%. The low false positives indicate their effectiveness in minimizing false alarms. The false-positive rate for k-Means is the highest (6.7%) compared to other methods, highlighting its limitations in properly distinguishing between legitimate inputs from anomalies.

Conclusion

This paper presents the comparative analysis of machine learning classifiers for graphical password authentication system. With superior accuracy, precision, and recall, Neural Networks and RNNs proved more effective for secure and reliable authentication. SVM also produced good results, taking a fair trade-off between computation burden and correct results. On the other hand, k-Means served its purpose of detecting anomalies by behaving differently within the dataset, however it had the downside of producing more false positive detections resulting in lower recall and lower precision on its own. These results highlight the fine balance that needs to be struck when choosing models and security versus usability needs. Further studies can explore hybrid methods which can improve the strength of the authentication method by taking advantage of the strengths of both the supervised and unsupervised methods.

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