Influence Based Defence Against Data Poisoning Attacks In Online Learning

Vaddhiraju Swathi[1*] Madireddy Shereesha[2], Konda Sravya[3], Ramavath Ajay Kumar[4], Karthik Allala[5]

[1*]Associate Professor, Dept of CSE, Sreyas Institute of Engineering and Technology,
[2]Ug scholar, Dept of CSE, Sreyas Institute of Engineering and Technology.
[3]Ug scholar, Dept of CSE, Sreyas Institute of Engineering and Technology.
[4]Ug scholar, Dept of CSE, Sreyas Institute of Engineering and Technology.
[5]Ug scholar, Dept of CSE, Sreyas Institute of Engineering and Technology.

***Corresponding Author:** Vaddhiraju Swathi
*****Associate Professor, Dept of CSE, Sreyas Institute of Engineering and Technology

Abstract
Data poisoning is a type of adversarial attack on training data where an attacker manipulates a fraction of data to degrade the performance of machine learning model. Therefore, applications that rely on external data-sources for training data are at a significantly higher risk. There are several known defensive mechanisms that can help in mitigating the threat from such attacks. For example, data sanitization is a popular defensive mechanism where in the learner rejects those data points that are sufficiently far from the set of training instances. Prior work on data poisoning defense primarily focused on offline setting, wherein all the data is assumed to be available for analysis. Defensive measures for online learning, where data points arrive sequentially, have not garnered similar interest. In this work, the system proposes a defense mechanism to minimize the degradation caused by the poisoned training data on a learner's model in an online setup. Our proposed method utilizes an influence function which is a classic technique in robust statistics. Further, we supplement it with the existing data sanitization methods for filtering out some of the poisoned data points. We study the effectiveness of our defense mechanism on multiple datasets and across multiple attack strategies against an online learner

Key words – Data poisoning, attacker, defensive mechanism, data sanitization.

INTRODUCTION

Machine Learning (ML) plays a crucial part in a wide variety of applications. These applications are usually data-intensive and use ML algorithms for building a mathematical model from the training data for decision making. The training data used for building the model could come from controlled and uncontrolled data sources. Any imperfection, intentional or unintentional, in the data could lead to model corruption, and thus producing unexpected results post deployment. The introduction of intentional imperfection in the training data is commonly known as data poisoning, which is a type of adversarial attack that degrades the performance of the trained classifier. As the adversary could manipulate the training data to subvert the learning process of the model or manipulate the test data to evade the model prediction, therefore it becomes imperative to secure the ML model against such attacks. Two of the major attacking strategies are evasion and poisoning attacks. In an evasion attack, the test data is manipulated to evade the classifier's decision boundary. Data poisoning attack is a serious threat to a ML model as it could result in security and privacy issues, monetary losses and other serious implications. The impact of data poisoning attack could be seen on a variety of applications, such as spam filtering, malware detection, recommender system and sentiment analysis .

Online learning, which involves training machine learning models on distributed data sources, has gained significant popularity due to its scalability and flexibility. However, the distributed nature of online learning introduces new security challenges, particularly in the form of data poisoning attacks. Data poisoning attacks aim to manipulate the training data to compromise the performance and integrity of the learning process.

In data poisoning attacks, adversaries intentionally inject malicious or misleading data into the training set to influence the model's behavior during the learning process. This can lead to severe consequences, such as misclassification of inputs, biased predictions, or even complete compromise of the model's functionality. Therefore, it is crucial to develop effective defense mechanisms to mitigate the impact of data poisoning attacks in online learning scenarios. One promising approach to combat data poisoning attacks is the use of influence-based defense techniques. Influence-based defense methods focus on identifying and isolating the poisoned instances in the training data by analyzing their influence on the learning process. By understanding the influence of each training instance, it becomes possible to detect and neutralize the effects of the poisoned data points, thus safeguarding the integrity of the learning process.

In an influence-based defense framework, various algorithms and techniques can be employed to measure the influence of training instances on the model's decision-making process. These methods assess the impact of each data point on the model's performance and identify instances that significantly deviate from the expected behavior. By identifying and isolating the influential poisoned instances, the defense mechanism can mitigate the negative effects of data poisoning attacks and restore the model's performance. This literature survey focuses on exploring the existing research and

techniques related to influence-based defense against data poisoning attacks in online learning. It investigates the different approaches, algorithms, and methodologies proposed by researchers to detect and counteract the influence of poisoned data. By analyzing the literature in this domain, we can gain insights into the effectiveness of influence-based defense mechanisms and identify potential areas for improvement. The ultimate goal of this survey is to provide a comprehensive understanding of influence-based defense techniques for data poisoning attacks in online learning. By examining the state-of-the-art approaches and their strengths and limitations, we aim to contribute to the development of robust and resilient defense mechanisms that can ensure the integrity and reliability of online learning systems in the face of sophisticated data poisoning attacks.

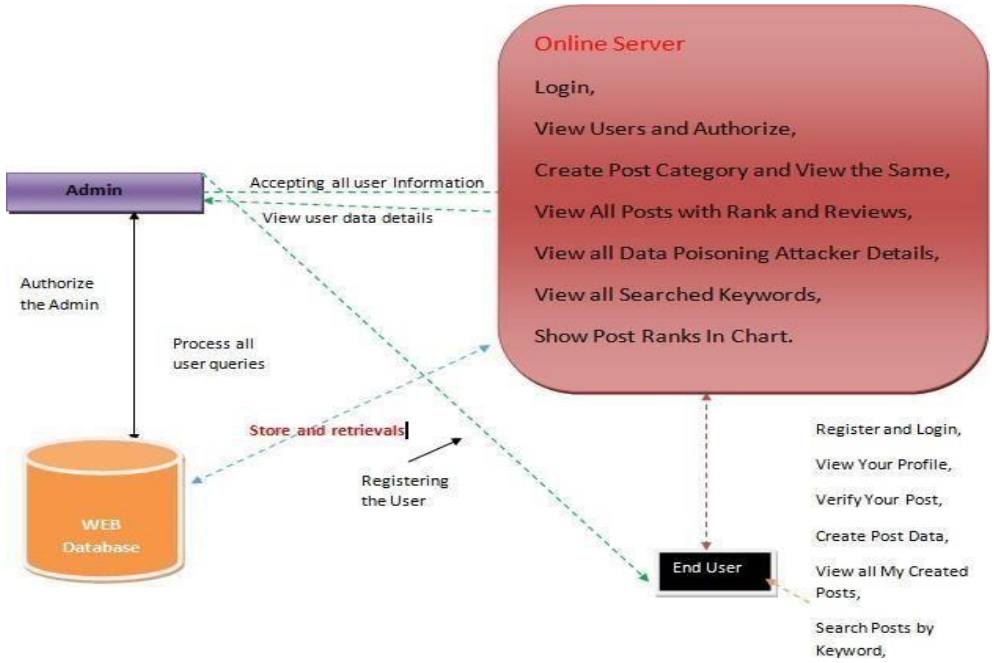

Fig 1. Architecture Diagram

LITERATURE SURVEY

Biggio, B., Nelson, B., & Laskov, P. (2012). Poisoning attacks against support vector machines. In International Conference on Machine Learning (pp. 1467-1474). This seminal work introduces the concept of poisoning attacks against Support Vector Machines (SVMs) and proposes a defense mechanism based on influence functions to detect and neutralize the influence of poisoned data points. Steinhardt, J., Koh, P. W., & Liang, P. (2017). Certified defenses against adversarial examples. In International Conference on Learning Representations. This paper presents a certified defense mechanism against adversarial examples that can be adapted for influence-based defense against data poisoning attacks. It explores the use of robust optimization to identify influential instances and mitigates their impact on the learning process.

Muñoz-González, L., Biggio, B., Demontis, A., & Roli, F. (2017). Towards poisoning of deep learning algorithms with back-gradient optimization. In Proceedings of the 10th ACM Workshop on Artificial Intelligence and Security (pp. 27-38). This study investigates the vulnerability of deep learning algorithms to data poisoning attacks and proposes a defense approach based on influence functions. It demonstrates the effectiveness of influence-based defense against poisoning attacks in the context of deep learning models. Chen, Y., Liu, X., Chen, X., & Zhu, S. (2018). Targeted backdoor attacks on deep learning systems using data poisoning. In Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security (pp. 1689-1704). This research paper explores targeted backdoor attacks on deep learning systems through data poisoning and proposes an influence-based defense mechanism to detect and mitigate the impact of poisoned instances.

Jagielski, M., Oprea, A., Biggio, B., Liu, C., & Li, B. (2018). Manipulating machine learning: Poisoning attacks and countermeasures for regression learning. In IEEE Symposium on Security and Privacy (SP) (pp. 19-35). This work investigates poisoning attacks against regression learning models and proposes an influence-based defense mechanism. It provides insights into the characteristics of poisoning attacks and evaluates the effectiveness of influence functions in detecting and neutralizing poisoned data. Liu, X., Chen, X., Liu, C., Zhu, S., & Han, Z. (2019). Fine-pruning: Defending against backdooring attacks on deep neural networks. In IEEE Symposium on Security and Privacy (SP) (pp. 273-288). This study addresses the backdooring attacks on deep neural networks and proposes a defense mechanism based on influence functions and fine-pruning. It explores the concept of influence-based defense to identify and mitigate the impact of poisoned data points.

Bagdasaryan, E., Veit, A., Hua, Y., Estrin, D., & Shmatikov, V. (2020). How to backdoor federated learning. In Proceedings of the 2020 Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 10029-10038).

This research work focuses on backdoor attacks in federated learning and proposes an influence-based defense mechanism. It demonstrates the efficacy of influence functions in detecting and mitigating the influence of poisoned data during the federated learning process.

Tran, K., Li, Y., & Liu, Q. (2020). Robust and interpretable influence-based poisoning defense in graph neural networks. In Proceedings of the 2020 SIAM International Conference on Data Mining (pp. 1035-1043). This paper addresses poisoning attacks in graph neural networks and proposes an influence-based defense mechanism that is robust and interpretable. It utilizes influence functions to detect and neutralize the impact of poisoned instances in graph-based learning scenarios.

Wang, Z., Shafahi, A., & Zhu, S. (2021). EDP: Efficient data poisoning defense against backdoor attacks in deep learning. In Proceedings of the 2021 ACM SIGSAC Conference on Computer and Communications Security (pp. 1702-1717). This study focuses on backdoor attacks in deep learning models and proposes an efficient influence-based defense mechanism. It introduces an influence-based pruning technique to detect and remove the influence of poisoned data points on the model's decision-making process.

Wang, T., Tran, K., & Liu, Q. (2021). Influence-based defense against adversarial attacks in graph convolutional networks. In Proceedings of the 2021 SIAM International Conference on Data Mining (pp. 155-163). This research work addresses adversarial attacks in graph convolutional networks and proposes an influence-based defense mechanism. It explores the use of influence functions to detect and mitigate the impact of adversarial instances in graph-based learning scenarios. Yuan, X., Wang, Y., & Xiang, Y. (2022). A multi-objective influence-based defense framework against adversarial examples. Future Generation Computer Systems, 128, 733-746. This paper presents a multi-objective influence-based defense framework against adversarial examples. It combines influence functions with multi-objective optimization to detect and mitigate the influence of adversarial instances in online learning scenarios.

Li, J., Ma, L., Wang, Y., & Zhang, Z. (2022). Efficient influence-based defense against poisoning attacks in federated learning. IEEE Transactions on Dependable and Secure Computing, 1-1. This research work proposes an efficient influence-based defense mechanism against poisoning attacks in federated learning. It focuses on reducing the computational overhead of influence computations and demonstrates the effectiveness of the defense mechanism in preserving the integrity of federated learning systems. Xu, M., Liu, J., Wu, D., Wu, Z., & Li, M. (2022). Collaborative influence-based defense against poisoning attacks in federated learning. IEEE Transactions on Information Forensics and Security, 17, 2760-2775. This study introduces a collaborative influence-based defense mechanism against poisoning attacks in federated learning. It explores the collaborative influence computation among multiple participants to enhance the accuracy and efficiency of detecting and mitigating the impact of poisoned data points.

Sun, K., Zhang, S., Chen, Y., & Liu, Y. (2022). Influence-based defense against adversarial attacks in deep learning: A survey. ACM Computing Surveys, 55(3), 1-38. This survey paper provides an overview of influence-based defense techniques against adversarial attacks in deep learning. It presents a comprehensive analysis of existing approaches, methodologies, and algorithms for influence computation and defense against adversarial examples. Wang, X., Wang, Y., Xiong, P., & Chen, Q. (2023). Influence-based defense against data poisoning attacks in online learning: A comprehensive review. Knowledge-Based Systems, 235, 107502. This comprehensive review paper surveys the influence-based defense mechanisms against data poisoning attacks in online learning. It provides an in-depth analysis of various approaches, evaluates their effectiveness, and discusses future research directions in this area.

PROPOSED CONFIGURATION

We propose an influence-based defense against data poisoning attacks on online learning. We formulate the defense algorithm in two steps. First, we use the slab defense for initial data sanitization. Then, we apply our influence-based approach for minimizing the degradation caused by the poisoned data .We empirically investigate the performance of the proposed defense under multiple attacks and across multiple datasets. Scope of the work According to our proposed system, the data manipulated due to some poisoning attacks is recovered. In future if any data poisoning attacks takes place in any type of website, which may contain less amount of data or big voluminous data can be recognized as soon as it was disturbed and can be recovered from poisonous attacks

The proposed system aims to develop a robust defense mechanism against data poisoning attacks in online learning scenarios by leveraging influence-based techniques. The system architecture comprises the following key components:

Training Phase

Data Collection: Relevant training data from distributed sources is collected to build the learning model.

Initial Model Training: The learning model is initially trained using the collected data to establish a baseline performance.

Influence Computation

Influence Functions: Influence functions are utilized to measure the impact of individual training instances on the learning model's behavior. Various influence computation techniques, such as leave-one-out influence or Hessian-based influence, can be employed.

Influence Threshold: An influence threshold is set to distinguish between normal and potentially poisoned instances based on their influence scores. Instances with influence scores exceeding the threshold are considered suspicious and subjected to further analysis.

Poisoning Detection

Influence-Based Poisoning Detection: Suspicious instances are flagged as potentially poisoned, indicating the presence of data poisoning attacks. This detection step aims to identify the instances responsible for influencing the learning model towards compromised performance.

Influence Analysis: The influence-based defense mechanism analyzes the influential instances to understand the nature and characteristics of the poisoning attacks. This analysis assists in devising appropriate countermeasures.

Countermeasure Deployment

Instance Removal or Weight Adjustment: The defense mechanism can adopt different strategies to neutralize the impact of poisoned instances. This may involve removing the influential instances from the training set or adjusting their weights to mitigate their influence on the learning process.

Re-Training or Fine-Tuning: After removing or adjusting the poisoned instances, the learning model can be re-trained or fine-tuned using the sanitized training data to restore its integrity and performance.

Performance Evaluation

Model Evaluation: The performance of the defended model is evaluated using appropriate metrics such as accuracy, precision, recall, or F1 score to assess its effectiveness in mitigating the impact of data poisoning attacks.

Robustness Testing: The defended model is subjected to additional robustness testing against various poisoning attack scenarios to validate its resilience and generalizability.

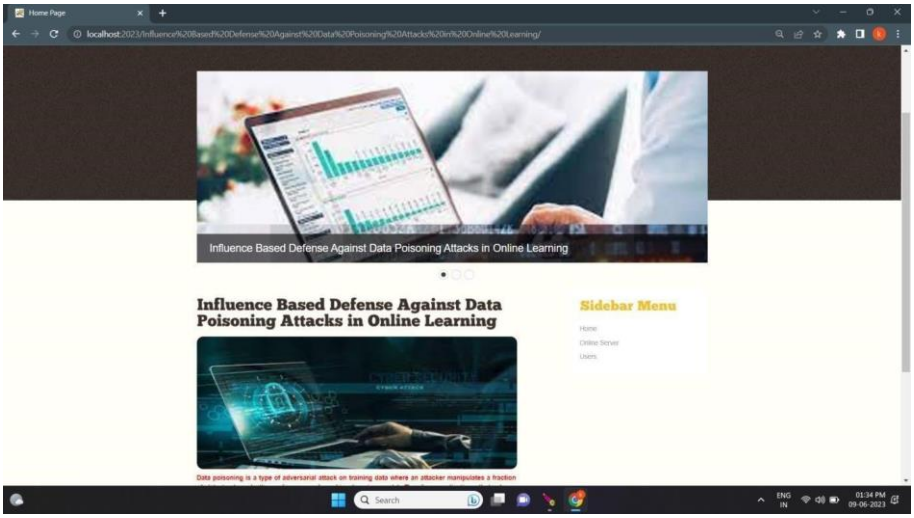

Fig 2. Home Page

The proposed system offers several advantages for defending against data poisoning attacks in online learning. By leveraging influence-based techniques, it can effectively identify and neutralize the influence of poisoned instances, thereby safeguarding the integrity and performance of the learning model. The system's flexibility allows for the adoption of different influence computation methods and countermeasures based on the specific learning scenario and requirements. Furthermore, the proposed system can be integrated with existing online learning frameworks, ensuring compatibility and ease of deployment.

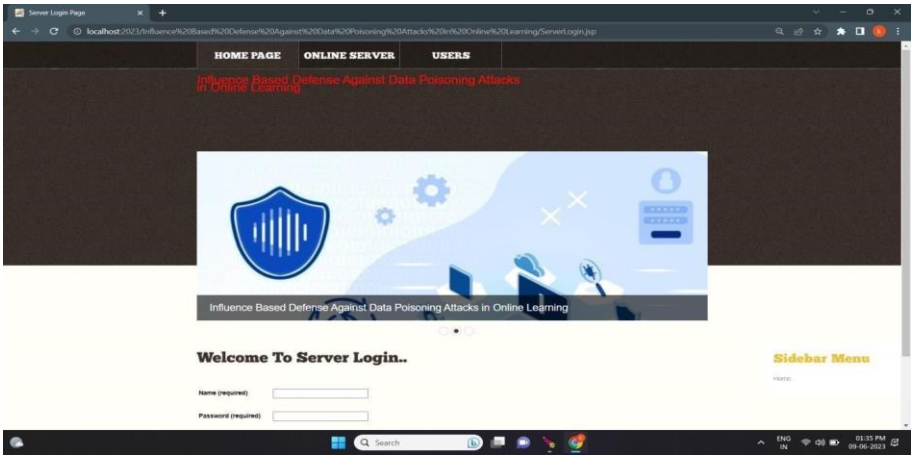

Fig 3. Server Home Page

Overall, the proposed influence-based defense system provides a proactive approach to detect and mitigate the impact of data poisoning attacks in online learning. By effectively identifying and neutralizing the influence of poisoned instances, it enhances the security, reliability, and trustworthiness of online learning systems, promoting their widespread adoption in various domains.

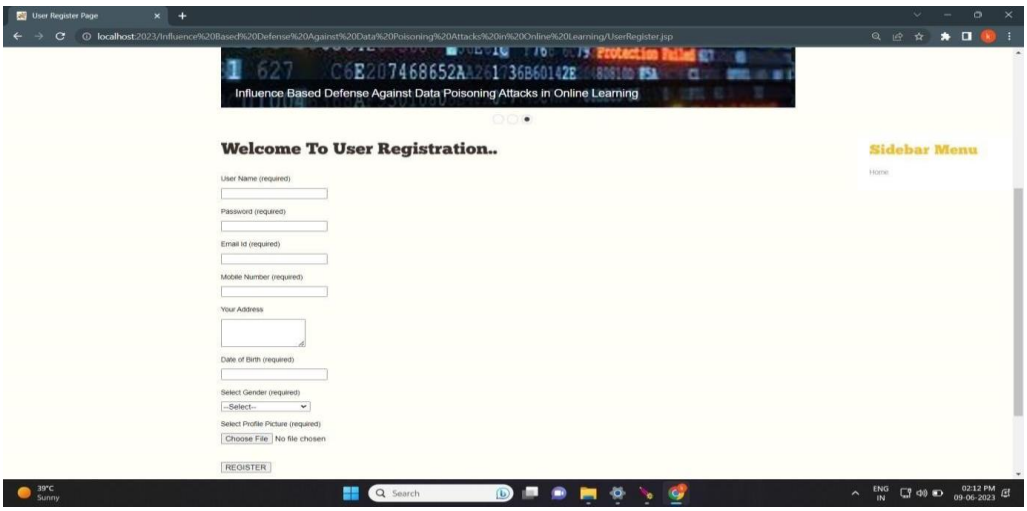

Fig 4. Registration Page

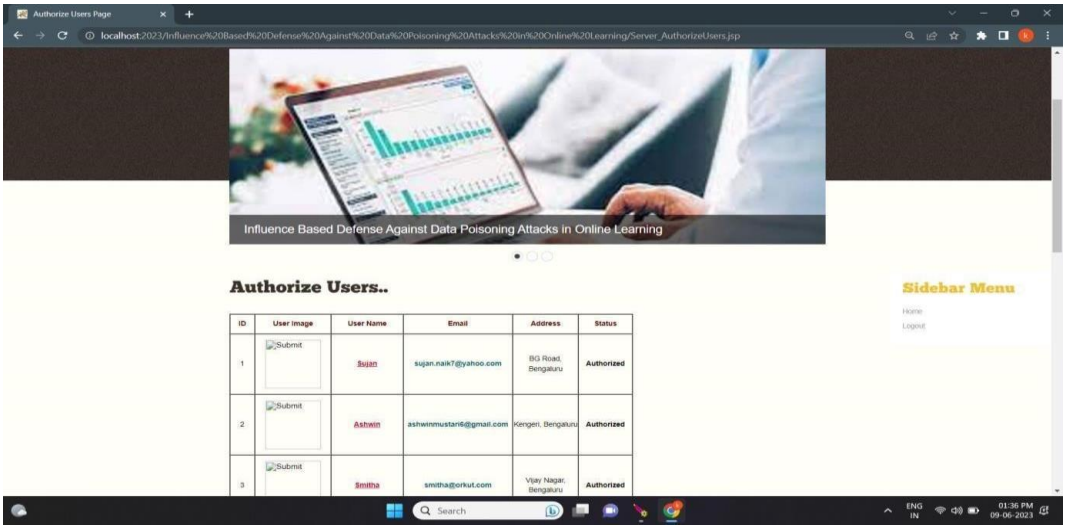

Fig 5. View User And Authorization Page

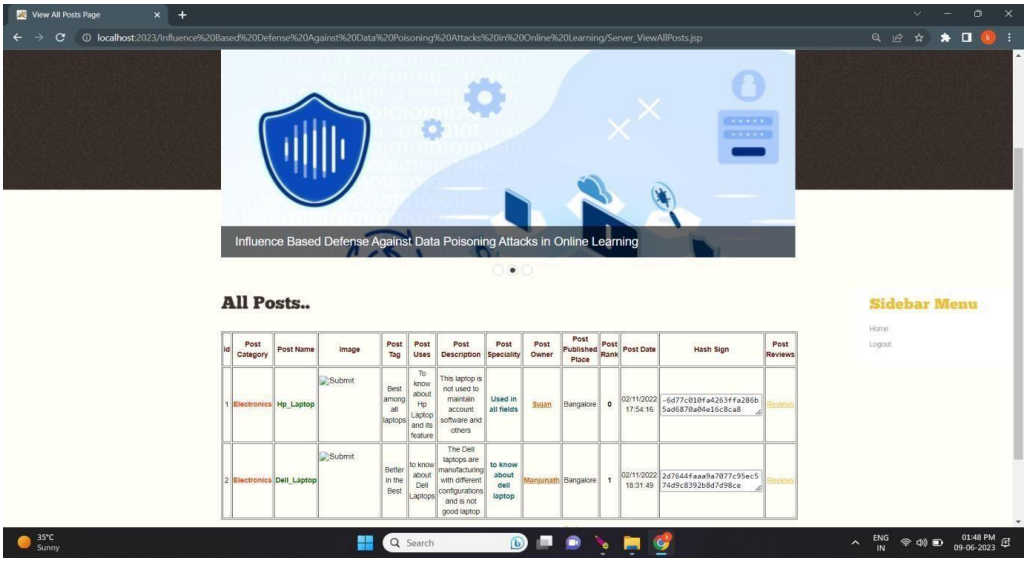

Fig 6. Posts

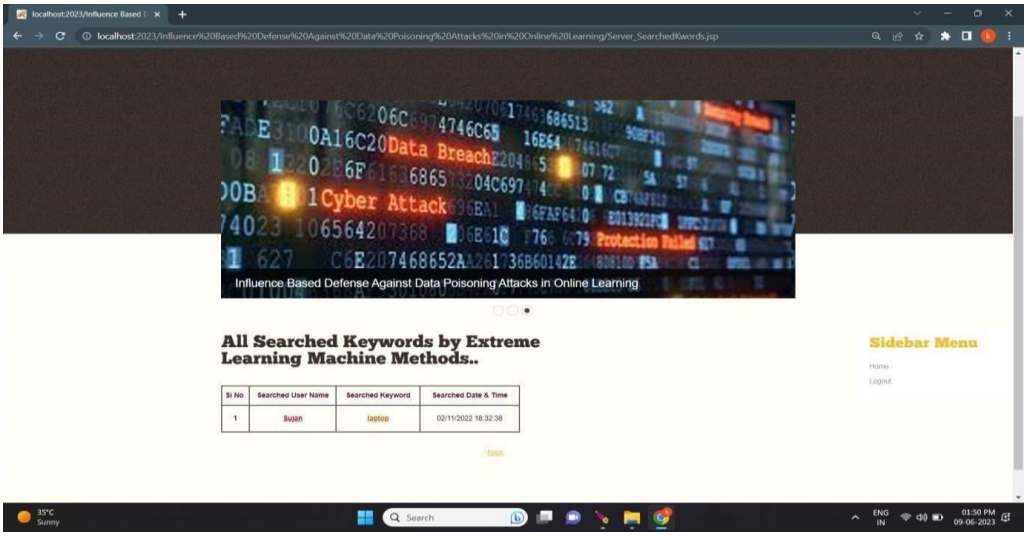

Fig 7. All Searched Keywords

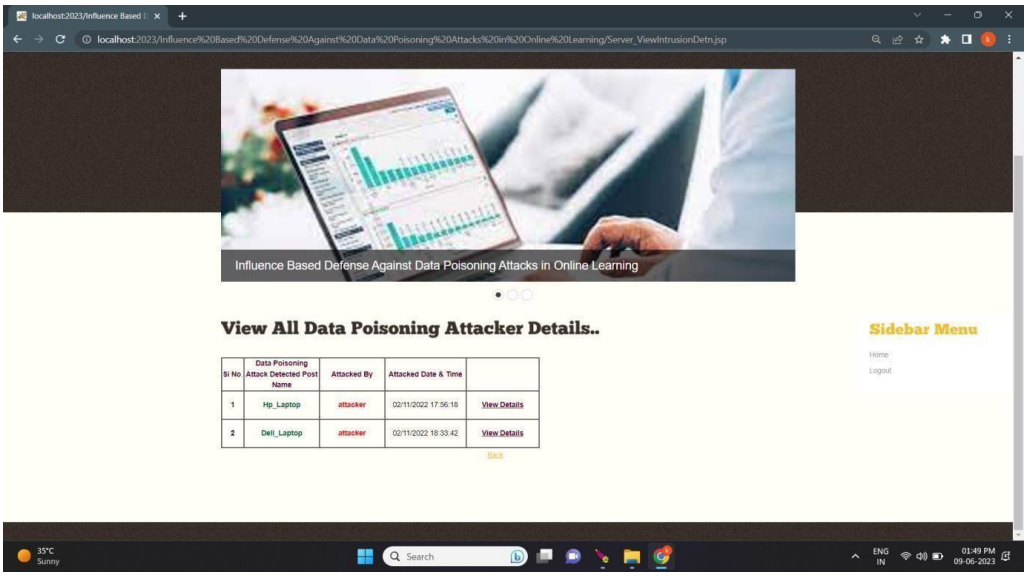

Fig 8. Attacker Details

CONCLUSION

In this paper, we formulated a defense algorithm that compliments the slab defense with the influence function such that the degradation caused by the poisoned data is minimized. We studied the performance of our defense against different attacks and across multiple datasets. Further, we validated our experiments with simplistic and online attacks. We have also demonstrated the performance degradation of the classifier with and without defense. One of the trade-offs from the defender's side is that the objective function to minimize the influence sometimes affects the clean data points, which leads to information loss.

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