



# DETECTING CYBER SECURITY THREATS USING MACHINE LEARNING

<sup>1</sup>M. Sreenivasu, <sup>2</sup>B.Srinivasa Rao, <sup>3</sup>T.Venkata Subba Rao, <sup>4</sup>N.Naveen, <sup>5</sup>L.Chaitanya Sai, <sup>6</sup>S.Sai Ganesh

<sup>1</sup>Associate Professor, <sup>2</sup>Assistant Professor, <sup>3,4,5,6</sup>UG Students

Department of Information Technology,  
GIET Engineering College, Rajamahendravaram, Andhra Pradesh, India - 533296

**Abstract :** The escalating complexity and volume of cyberattacks pose a significant threat to individuals, organizations, and critical infrastructure. Machine learning techniques offer a powerful tool in combating these threats by enabling proactive detection and mitigation. This project specifically employs the random forest algorithm to enhance cybersecurity threat detection. Random forests, consisting of an ensemble of decision trees, are renowned for their robustness and accuracy in classification tasks. The model is trained on a comprehensive dataset of cybersecurity threats, learning to discern patterns indicative of malicious activity. The trained model can then analyze network traffic, system logs, or other relevant data to identify potential cyberattacks in real-time. This project aims to improve detection rates 96% and reduce false positives compared to traditional signature-based cybersecurity systems.

**Keywords:** *Cybersecurity, Machine Learning, Random Forest Algorithm, Threat Detection, Proactive, Ensemble Learning, Decision Trees, Classification, Robustness, Accuracy, Dataset, Malicious Activity, Network Traffic Analysis, Real-Time Detection, False Positives, Signature-Based Systems*

## 1. INTRODUCTION

Cyberspace, the global environment facilitating electronic resource sharing, encompasses diverse elements like the Internet, skilled users, system resources, and data. Its significance has surged post-2017, marked by an 81% increase in internet usage in developed nations and continued global growth. This growth offers unparalleled access to information but also spawns cyber threats and crimes. Cybersecurity, a critical response to these risks, encompasses technologies, experts, and processes aimed at safeguarding cyberspace. It undergoes constant enhancements to counter evolving cybercriminal tactics. As cyberspace evolves, cybersecurity must adapt, ensuring the safety of electronic resources and the integrity of global information exchange. In today's interconnected world, cybersecurity threats are a constant and evolving danger. Hackers, cybercriminals, and state-sponsored actors continuously develop sophisticated techniques to compromise networks, steal data, and disrupt operations. Traditional signature-based cybersecurity solutions often struggle to keep pace with these dynamic threats, leaving systems vulnerable to zero-day attacks and unknown exploits. Machine learning (ML) has emerged as a transformative technology in the realm of cybersecurity. By leveraging the power of algorithms and statistical models, ML systems can analyze vast amounts of data, identify subtle patterns, and detect anomalies that might indicate malicious activity.

The random forest algorithm, in particular, offers compelling advantages due to its ability to handle complex datasets, resist overfitting, and yield accurate classifications. This project harnesses the potential of the random forest algorithm to build a robust cybersecurity threat detection system. By training on a comprehensive dataset of known cyberattacks, the model learns to distinguish between benign and malicious patterns within network traffic, system logs, or other relevant sources. This proactive approach enables the detection of both known and emerging threats, significantly enhancing cybersecurity posture and mitigating the risk of costly breaches. Cyber threats encompass various acts aiming to steal information, violate integrity rules, or harm computing devices/networks. They include phishing, malware, IoT attacks, denial of service, spam, intrusion, financial fraud, and ransomware. This paper focuses on malware detection, intrusion detection, and spam detection. Spam emails, unwanted or unsolicited, clutter networks and consume resources. Malware, encompassing viruses, worms, ransomware, etc., disrupts systems and data. Intrusions scan network vulnerabilities, countered by Intrusion Detection Systems (IDS), classified as signature-based,

anomaly-based, or hybrid. These threats underscore the critical need for robust cybersecurity measures to safeguard cyberspace's integrity and functionality. In today's interconnected world, cybersecurity threats are a constant and evolving danger. Hackers, cybercriminals, and state-sponsored actors continuously develop sophisticated techniques to compromise networks, steal data, and disrupt operations. Traditional signature-based cybersecurity solutions often struggle to keep pace with these dynamic threats, leaving systems vulnerable to zero-day attacks and unknown exploits. Machine learning (ML) has emerged as a transformative technology in the realm of cybersecurity. By leveraging the power of algorithms and statistical models, ML systems can analyze vast amounts of data, identify subtle patterns, and detect anomalies that might indicate malicious activity. The random forest algorithm, in particular, offers compelling advantages due to its ability to handle complex datasets, resist overfitting, and yield accurate classifications. This project harnesses the potential of the random forest algorithm to build a robust cybersecurity threat detection system.

## 2. Literature Survey

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- Detection of Cyber Attack in Network by Using Machine Learning, proposed a system in June 2022. Cyber-crime is proliferating everywhere exploiting every kind of vulnerability to the computing environment. Ethical Hackers pay more attention towards assessing vulnerabilities and recommending mitigation methodologies. The development of effective techniques has been an urgent demand in the field of the cyber security community. Most techniques used in today's IDS are not able to deal with the dynamic and complex nature of cyber-attacks on computer networks. Machine learning for cyber security has become an issue of great importance recently due to the effectiveness of machine learning in cyber security issues. Machine learning techniques have been applied for major challenges in cyber security issues like intrusion detection, malware classification and detection, spam detection and phishing detection.
- Kandadai Bhargavi, Vadivelan Natarajan " Detection of cyber attacks using machine learning " , proposed a system in April 2022. Cyber security professionals pay greater regard to risk evaluation and propose techniques for mitigating. Throughout the area of cyber defense, designing successful strategies was a plan set. Machine learning is also increasingly becoming an important concern in data protection although machine learning is successful in cyber defense. The rapid

expansion in Cloud Computing, networking and evolutionary computation has been the result of unprecedented developments in computing, storage and computational technology. The planet is rapidly being digitized - there is a growing want of comprehensive and sophisticated information security and privacy issues And Strategies to fight security threats, which are becoming more complicated. Cyber terrorism is spreading worldwide using all kinds of computer weakness. Machine learning algorithms were used to address global computer security threats such as malware detection, ransomware recognition, fraud detection and spoofing identification.

- Kamran Shaukat , Suhuai Luo “ Cyber Threat Detection Using Machine Learning Techniques ”, proposed a system in 2020. The present-day world has become all dependent on cyberspace for every aspect of daily living. The use of cyberspace is rising with each passing day. The world is spending more time on the Internet than ever before. As a result, the risks of cyber threats and cyber crimes are increasing. The term 'cyber threat' is referred to as the illegal activity performed using the Internet. Cybercriminals are changing their techniques with time to pass through the wall of protection. Conventional techniques are not capable of detecting zero-day attacks and sophisticated attacks. Thus far, heaps of machine learning techniques have been developed to detect cybercrimes and battle against cyber threats.

### 3. OVERVIEW OF THE SYSTEM

#### 3.1 Existing system

In Existing system Signature-Based Detection relies on a database of known attack patterns (signatures). This approach is effective against well-understood threats but struggles with zero-day attacks and novel attack variants. These systems may use manually defined rules to identify suspicious activity. Rule-based systems can be inflexible, leading to missed threats and a high rate of false positives. Existing systems might include basic anomaly detection, but often with less sophisticated methods, leading to less accurate results. Cyber threats comprise a range of activities with the intention of compromising information, violating integrity, or causing harm to computing systems. Examples include phishing, malware, IoT attacks, denial of service, spam, intrusion, financial fraud, and ransomware. This study specifically addresses the detection of malware, intrusions, and spam. Spam emails, often unsolicited, congest networks and deplete resources. Malware, such as viruses, worms, and ransomware, disrupts systems and compromises data integrity. Intrusions involve scanning network vulnerabilities and are countered by Intrusion Detection Systems (IDS), which come in signature-based, anomaly-based, or hybrid forms. The prevalence of these threats underscores the critical importance of implementing robust cybersecurity measures to ensure the integrity and functionality of cyberspace.

#### 3.2 Proposed system

In Proposed System Proactive Detection the ML model learns to identify attack patterns even without predefined signatures, enabling the detection of new and complex threats. Retraining the model with new data maintains effectiveness against evolving threats. The random forest algorithm excels at identifying deviations from normal behavior, a hallmark of cyberattacks. With the focus on broader patterns rather than rigid rules, the system can generate more accurate alerts. The proposed system utilizes Proactive Detection, employing Machine Learning (ML) to discern attack patterns autonomously, without relying on predefined signatures. This capability enables the identification of novel and intricate threats. Regular retraining of the ML model with fresh data ensures its efficacy against evolving threats. Leveraging the random forest algorithm, the system excels at spotting anomalies in behavior, a characteristic of cyberattacks. By prioritizing broader patterns over rigid rules, the system can produce more precise alerts, enhancing its overall effectiveness in threat detection and mitigation.

- Improved ability to identify a wider range of cyberattacks, including zero-day exploits.
- Lower Maintenance
- Reduced reliance on constant signature updates.
- Fewer false positives help streamline security workflows for IT teams.
- Provides valuable data to understand threat patterns and inform cybersecurity strategies.
- The system boasts enhanced capabilities in identifying a broader spectrum of cyberattacks, even those involving zero-day exploits.
- Its proactive detection approach reduces the need for frequent maintenance, as it doesn't heavily rely on constant signature updates.
- By minimizing false positives, the system streamlines security workflows for IT teams, allowing them to focus on genuine threats.
- Moreover, it offers valuable insights into threat patterns, empowering organizations to refine their cybersecurity strategies.
- This comprehensive approach not only strengthens defense against known threats but also enables proactive mitigation against emerging ones.

- The system's reduced maintenance requirements translate to cost savings for organizations while maintaining a high level of security.
- Its ability to adapt to evolving threats while providing actionable intelligence positions it as a valuable asset in today's cybersecurity landscape.

### 3.3 Software Requirements:

Operating System	:	Windows 10
Coding Language	:	Python 10
IDE	:	VSCode
Libraries	:	Pandas,Matplotlib

### 3.4 Hardware Requirements:

Processor	:	Dual-core or higher
RAM	:	4GB or more
Storage	:	At least 100GB
Display	:	Minimum 1024 x 768 resolution
Network	:	Integrated Ethernet or Wi-Fi
Mouse and Keyboard	:	Standard peripherals

## 4. Technologies Used

### 4.1 Python

High-level programming languages like Python are popular because of their readability, ease of use, and versatility. Since its initial release in 1991, Python which Guido van Rossum developed has risen to rank among the most widely used computer languages worldwide. Its popularity is a result of a number of essential qualities and features that make it perfect for a variety of uses. Python's readability and ease of learning are two of its key characteristics. Its syntax is intended to be simple and easy to comprehend, so programmers of all skill levels can use it. Python reduces syntactical clutter and improves code readability by using indentation to define code chunks. Python's interpretive nature makes it possible for interactive development and quick prototyping. The Python interpreter runs code line by line, making it fast for developers to test and make changes to their code. Python is popular in educational settings and among developers who value experimentation and productivity because of its interactive nature. Python is a high-level language, which means that it has built-in functions and data structures and abstracts away complicated operations. By eliminating unnecessary details, this abstraction streamlines coding chores and frees up developers' time to concentrate more on solving problems. Furthermore, variable types are determined at runtime via Python's dynamic typing feature, which allows for flexibility and simple code but necessitates careful management of variable types to prevent mistakes. A substantial standard library that includes modules and packages for a variety of activities, including file I/O, networking, mathematics, and more, is included with the language. In many situations, this extensive standard library eliminates the need for external dependencies and improves Python's functionality in a variety of fields. Because Python is platform-independent, programs written in it can run without change on a variety of operating systems, including Windows, macOS, Linux, and others. This portability guarantees uniform behavior across many operating systems and is beneficial for creating cross-platform apps. The concepts of object-oriented programming (OOP), such as classes, inheritance, encapsulation, and polymorphism, are supported by Python. These OOP ideas make it easier to write modular and reusable code, which enhances the structure and maintainability of the code. Another benefit of the language is the vibrant and sizable Python developer community, which produces frameworks, libraries, and other tools. Python's capabilities are extended for a wider range of applications, domains, and use cases via this dynamic ecosystem. Of course, the following is a list of further information on Python in paragraph form. Python's clear, straightforward syntax makes it easy to read and less complicated for novice programmers, while also encouraging code clarity for more seasoned writers. In addition to ensuring uniform formatting, the use of indentation for code blocks improves the code structure's readability and aesthetic appeal. Since readability makes code review, maintenance, and debugging easier, it's an essential component of collaborative projects involving numerous developers working on the same codebase. Furthermore, a vast array of pre-built modules and packages covering a wide variety of functionalities can be found in Python's huge standard library. Any process that requires you to work with data structures, manage files, execute mathematical operations, communicate with databases, or tackle network programming tasks may probably be completed more efficiently with a module from Python's standard library.

## 4.2 Pandas

Pandas is a Python library that provides high-performance, easy-to-use data structures and data analysis tools. It is widely used for data manipulation, cleaning, analysis, and visualization tasks in data science and machine learning projects. Pandas introduces the DataFrame data structure, which is a two-dimensional, size-mutable, and labeled tabular data structure with columns of potentially different types. This makes it easy to work with structured data, similar to working with a spreadsheet or SQL table. Pandas offers powerful tools for data manipulation, including indexing, slicing, filtering, merging, joining, and reshaping operations. These capabilities enable users to clean, transform, and preprocess datasets efficiently. Pandas provides a wide range of statistical functions and methods for data analysis, such as descriptive statistics, grouping, aggregation, and time series analysis. These functionalities enable users to gain insights into their data and extract valuable information. Pandas seamlessly integrates with other Python libraries and tools commonly used in data science workflows, such as NumPy, Scikit-learn, Matplotlib, and Jupyter notebooks. This allows for a cohesive and streamlined data analysis and modeling process. Pandas is optimized for performance, with underlying algorithms implemented in C or Cython. This ensures fast execution speeds, even when working with large datasets. Pandas is a versatile and powerful library for data manipulation and analysis, making it a fundamental tool in the toolkit of data scientists and machine learning practitioners.

## 4.3 Scikit-learn

Scikit-learn is a popular machine learning library for Python that provides simple and efficient tools for data mining and data analysis. It features various machine learning algorithms, preprocessing techniques, model evaluation tools, and utilities, making it suitable for a wide range of machine learning tasks. Scikit-learn includes a comprehensive collection of supervised and unsupervised learning algorithms, including classification, regression, clustering, dimensionality reduction, and ensemble methods. These algorithms are implemented with a consistent and user-friendly API, making them easy to use and compare. Scikit-learn offers a variety of preprocessing techniques for data normalization, scaling, encoding categorical variables, imputing missing values, and feature extraction. These preprocessing steps are essential for preparing data for machine learning models and improving their performance. Scikit-learn provides tools for evaluating the performance of machine learning models, such as cross-validation, grid search, hyperparameter tuning, and various metrics for classification, regression, and clustering tasks. These tools help users assess the generalization and robustness of their models. Scikit-learn integrates seamlessly with other Python libraries, such as Pandas, NumPy, and Matplotlib. This allows for seamless integration into existing data science workflows and facilitates data preprocessing, model training, and evaluation. Scikit-learn has a large and active community of users and developers, contributing to ongoing development, bug fixes, and improvements. Additionally, it offers comprehensive documentation, tutorials, and examples, making it accessible to users of all skill levels. Scikit-learn is a versatile and user-friendly library for machine learning, suitable for both beginners and experienced practitioners alike.

## 4.4 Vscode

Visual Studio Code (VS Code) is a widely used integrated development environment (IDE) developed by Microsoft. It has gained immense popularity among developers due to its lightweight yet powerful features, extensive customization options, and support for a wide range of programming languages and frameworks. VS Code is designed to enhance developers' productivity and streamline the coding experience across various platforms and projects. One of the key strengths of VS Code is its versatility and cross-platform compatibility. It runs seamlessly on Windows, macOS, and Linux operating systems, providing a consistent user experience regardless of the development environment. This flexibility allows developers to work on their preferred operating system and collaborate seamlessly with team members using different platforms.

## 4.5 Matplotlib

Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. It is widely used for data visualization and exploration in various fields, including data science, machine learning, scientific computing, and engineering. Matplotlib provides a wide range of plotting functions for creating basic and advanced visualizations, including line plots, scatter plots, bar plots, histograms, box plots, heatmaps, contour plots, and 3D plots. These functions offer extensive customization options for controlling colors, styles, labels, annotations, and axes properties. Matplotlib supports multiple output formats, including PNG, PDF, SVG, EPS, and interactive formats for web-based visualizations. This flexibility allows users to generate publication-quality figures for various purposes, such as presentations, reports, publications, and web applications. Matplotlib seamlessly integrates with Jupyter notebooks, providing interactive plotting capabilities and inline display of plots within notebook cells. This enables

users to visualize data and explore results interactively during the data analysis and modeling process. Matplotlib is highly extensible and customizable, allowing users to create custom plot types, styles, and backends tailored to their specific needs. Additionally, Matplotlib can be combined with other libraries, such as Seaborn and Plotly, to enhance its functionality and create more complex visualizations. Matplotlib has a large and active community of users and developers, contributing to ongoing development, support, and documentation efforts. It offers extensive documentation, tutorials, and examples, making it accessible to users of all skill levels. Matplotlib is a powerful and flexible library for creating a wide range of static and interactive visualizations in Python, essential for data exploration, analysis, and communication.

### ***Economical Feasibility:***

The economic feasibility of the proposed system lies in its ability to leverage proactive detection techniques, driven by machine learning, to enhance cybersecurity defenses. Initial investment will be required for developing and integrating machine learning models into existing infrastructure, along with ongoing costs for training and maintenance. However, these expenditures are justified by the potential benefits the system offers. By autonomously identifying novel and complex threats without relying on predefined signatures, the system can improve threat detection accuracy while minimizing false positives. This capability not only reduces the likelihood and impact of security breaches but also saves costs associated with investigating non-threatening events. Furthermore, the system's scalability and adaptability ensure its effectiveness against evolving threats over time, potentially reducing the need for costly manual intervention or system upgrades. Ultimately, the economic feasibility of the proposed system rests on its ability to deliver long-term value through improved threat detection, reduced false positives, and cost savings from avoided breaches.

### **Technical Feasibility**

The technical feasibility of the proposed system is rooted in the capabilities of machine learning algorithms, particularly the random forest algorithm, to autonomously discern attack patterns without the need for predefined signatures. This approach allows the system to adapt and identify new and complex threats effectively. Additionally, the system's architecture must be designed to handle the computational demands associated with real-time threat detection and the processing of large volumes of data. This may involve upgrading or investing in computational infrastructure capable of supporting machine learning models and ensuring timely response to potential threats. Furthermore, the system requires mechanisms for regular retraining with fresh data to maintain its effectiveness against evolving threats. Integration with existing cybersecurity infrastructure and protocols is essential to ensure seamless operation and compatibility with organizational workflows. Overall, while there may be technical challenges such as algorithm development, computational resource requirements, and integration complexities, the capabilities of machine learning, coupled with proper system design and implementation, make the proposed system technically feasible for enhancing cybersecurity defenses.

### **Social Feasibility**

The social feasibility of the proposed system involves assessing its acceptance and adoption by various stakeholders, including cybersecurity professionals, organizational leadership, and end-users. Firstly, gaining buy-in from cybersecurity professionals is crucial, as they will be responsible for implementing, managing, and monitoring the system. Providing training and education on the benefits and operation of the system can help alleviate concerns and garner support from this group.

Organizational leadership's support is essential for allocating resources and prioritizing cybersecurity initiatives. Demonstrating the potential cost savings from avoided breaches and the system's ability to enhance overall security posture can help secure executive sponsorship. End-user acceptance is also vital, particularly if the system impacts their daily workflows or introduces new security protocols. Clear communication about the purpose and benefits of the system, as well as transparent policies regarding data privacy and security, can help build trust and encourage adoption among end-users. Addressing potential social concerns, such as job displacement fears among cybersecurity professionals due to automation, is important. Emphasizing that the system complements human expertise rather than replacing it can help alleviate these concerns and foster a collaborative approach to cybersecurity. Overall, the social feasibility of the proposed system depends on effective communication, stakeholder engagement, and addressing any concerns or resistance to change. By garnering support from cybersecurity professionals, organizational leadership, and end-users, the system can be successfully implemented and integrated into existing cybersecurity practices, ultimately enhancing overall security effectiveness.

### 5. Architecture

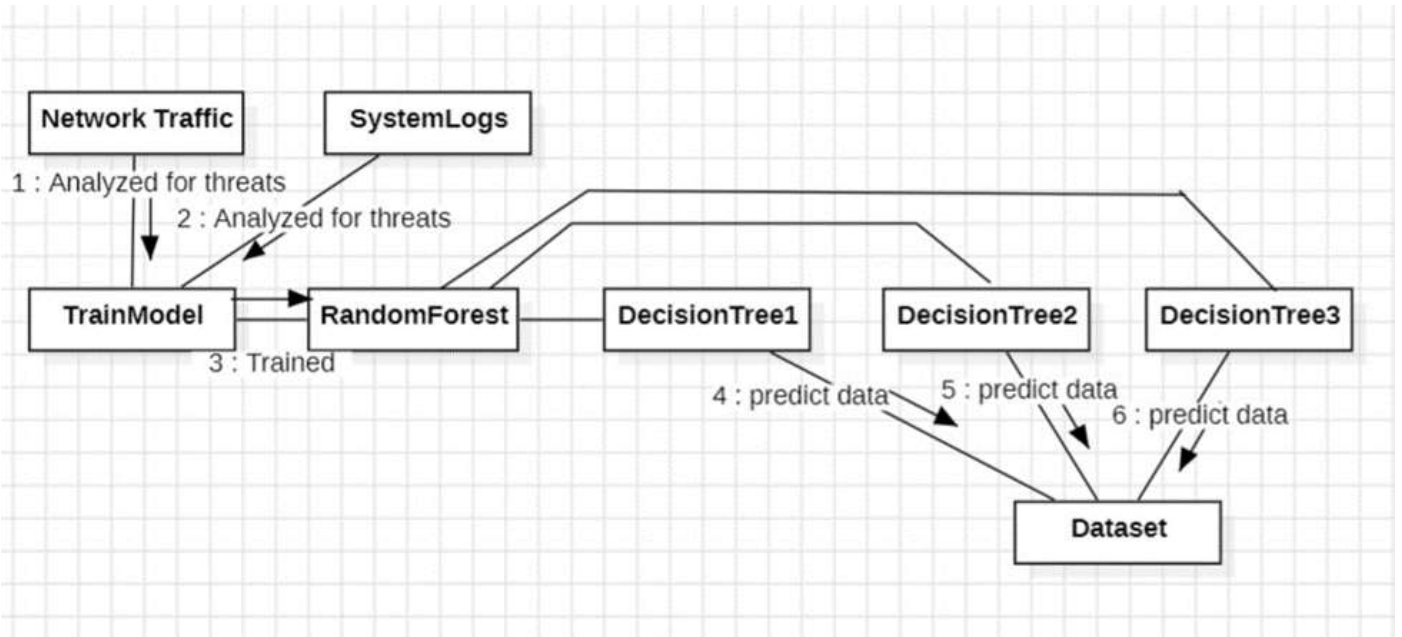


Fig 1: System Architecture

### 6. RESULTS SCREENSHOTS

#### Confusion Matrix

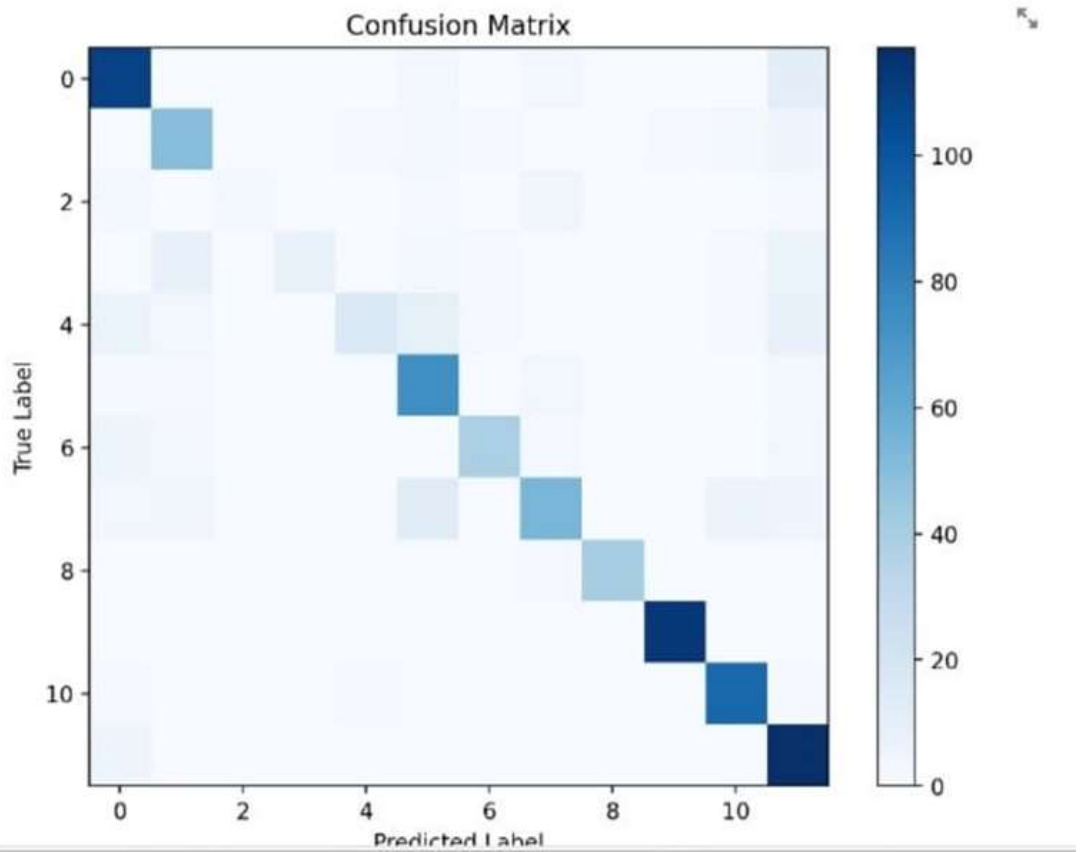


Fig 2: Confusion Matrix

# Feature Importance

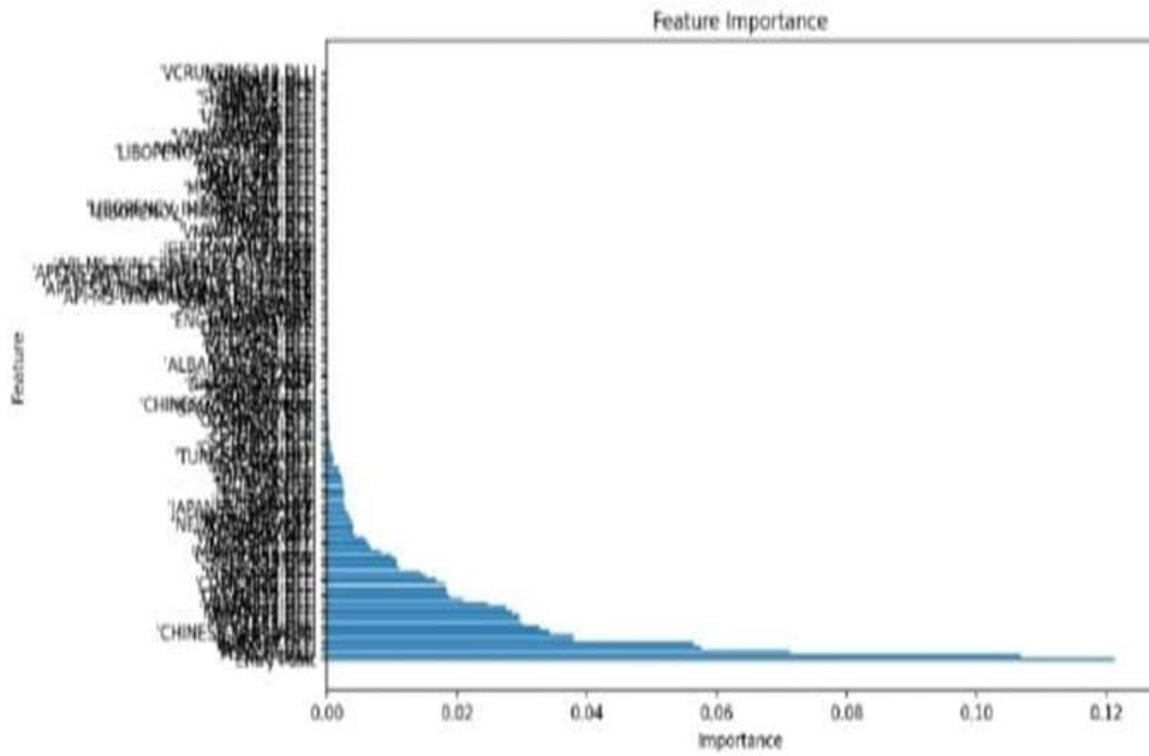


Fig 3: Feature Importance

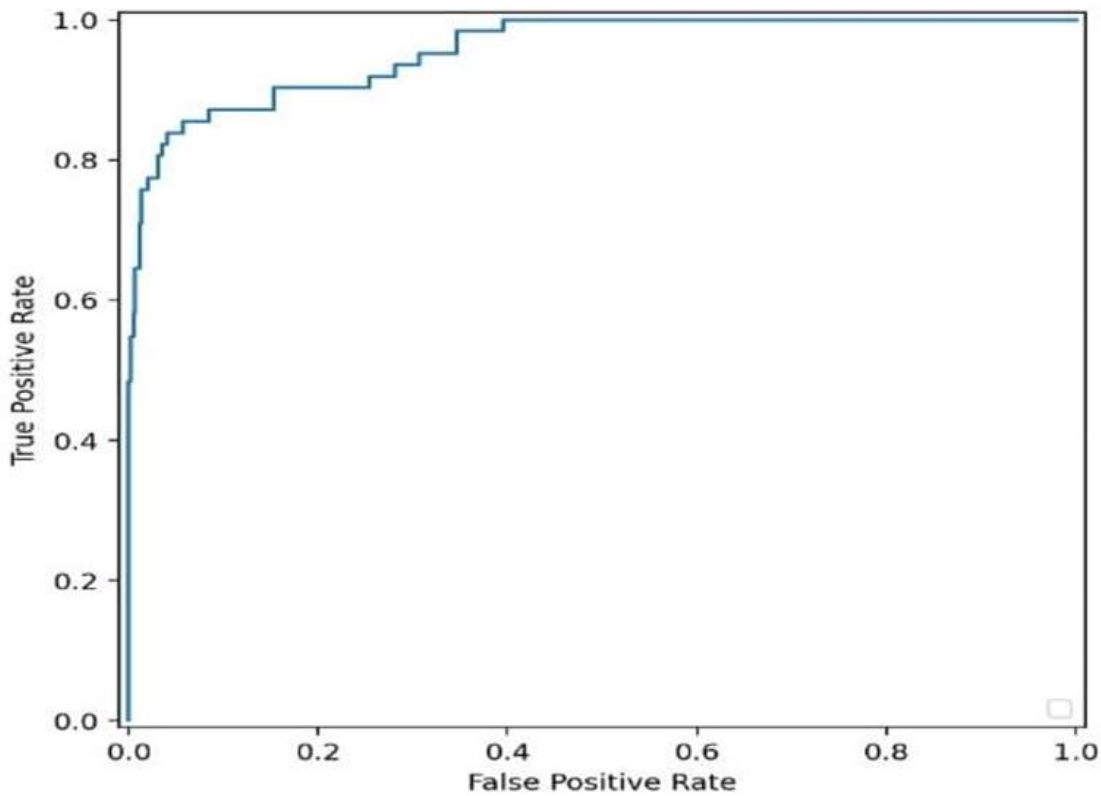
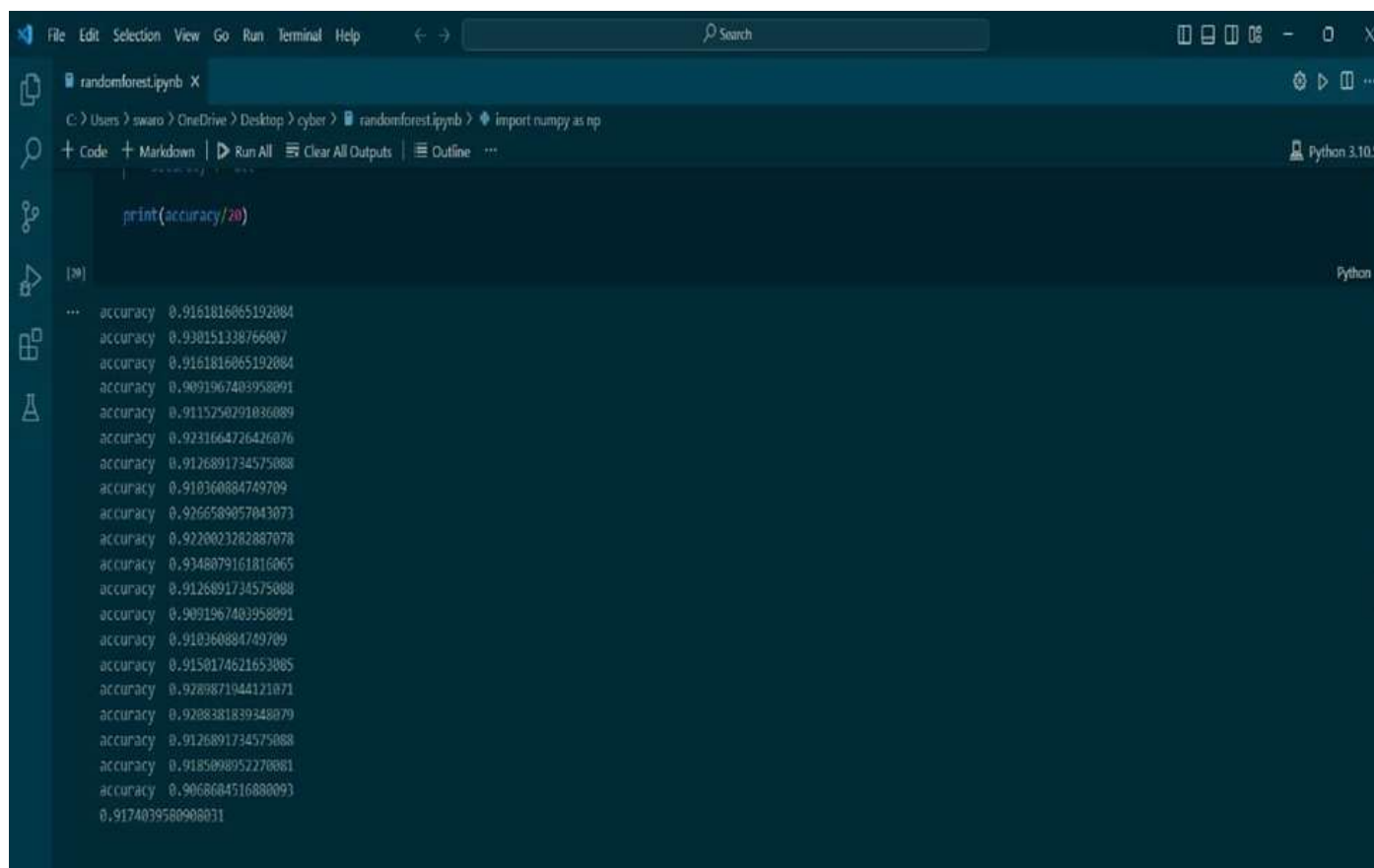


Fig 4: ROC Curve





```
File Edit Selection View Go Run Terminal Help
randomforest.ipynb X
C:\Users\swaro> OneDrive > Desktop > cyber > randomforest.ipynb > import numpy as np
+ Code + Markdown Run All Clear All Outputs Outline
Python 3.10.5

print(accuracy/20)

[ ]
Python

...
accuracy 0.9161816065192884
accuracy 0.930151338766007
accuracy 0.9161816065192884
accuracy 0.9091967403958091
accuracy 0.9115250291036089
accuracy 0.9231664726426076
accuracy 0.9126891734575088
accuracy 0.910360884749709
accuracy 0.9266589057043073
accuracy 0.9220023282887078
accuracy 0.9348079161816065
accuracy 0.9126891734575088
accuracy 0.9091967403958091
accuracy 0.910360884749709
accuracy 0.9150174621653085
accuracy 0.9289871944121071
accuracy 0.9288381839348079
accuracy 0.9126891734575088
accuracy 0.9185098952270881
accuracy 0.9066804516880093
0.9174039580908031
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Fig5: Output Screen

## 7. CONCLUSION

In conclusion, this project demonstrates the potential of machine learning, particularly the random forest algorithm, in enhancing cybersecurity threat detection capabilities. With the ever-increasing complexity and volume of cyberattacks posing significant challenges to individuals, organizations, and critical infrastructure, proactive detection and mitigation are essential. By leveraging the robustness and accuracy of random forests, trained on a comprehensive dataset of cybersecurity threats, this project aims to achieve a substantial improvement in detection rates while minimizing false positives compared to traditional signature-based systems. The utilization of machine learning techniques allows for the identification of patterns indicative of malicious activity, enabling the model to analyze network traffic, system logs, and other relevant data in real-time. Through continuous learning and adaptation, the system becomes adept at recognizing evolving cyber threats, thereby enhancing overall cybersecurity resilience. By focusing on enhancing detection rates and reducing false positives, this project contributes to strengthening cybersecurity posture and mitigating the risks posed by cyberattacks. Moving forward, further research and development in machine learning-based cybersecurity solutions will continue to play a crucial role in addressing the dynamic and evolving nature of cyber threats, ultimately safeguarding individuals, organizations, and critical infrastructure from potential harm.

## 8. FUTURE ENHANCEMENT

Advanced Ensemble Techniques Experimenting with combining the random forest model with other machine learning algorithms (e.g., boosting, neural networks) could further enhance accuracy and adaptability. Develop the system to analyze network traffic or system data in real-time, enabling immediate containment of detected threats. Behavioral Analytics - Incorporate user and entity behavior analysis (UEBA) concepts to create a more nuanced understanding of normal activity, further improving anomaly detection. Threat Intelligence Integration - Combine the ML model with external threat intelligence feeds to stay abreast of the latest attack methods

## 9. REFERENCES

- [1] "ICT Facts and Figures 2017", Telecommunication Development Bureau International Telecommunication Union (ITU) Technical Report.
- [2] F. Farahmand, S. B. Navathe, P. H. Enslow and G. P. Sharp, "Managing vulnerabilities of information systems to security incidents", Proceedings of the 5th international conference on Electronic commerce, pp. 348-354, 2003.
- [3] P. Szor, The Art of Computer Virus Research and Defense: ART COMP VIRUS RES DEFENSE \_p1, Pearson Education, 2005.
- [4] M. Jump, "Fighting Cyberthreats with Technology Solutions", Biomedical instrumentation technology, vol. 53, no. 1, pp. 38-43, 2019.
- [5] N. Kostyuk and C. Wayne, Communicating Cybersecurity: Citizen Risk Perception of Cyber Threats, 2019.
- [6] A. K. Jain, D. Goel, S. Agarwal, Y. Singh and G. Bajaj, "Predicting Spam Messages Using Back Propagation Neural Network", Wireless Personal Communications, vol. 110, no. 1, pp. 403-422, 2020.
- [7] N. Sultana, N. Chilamkurti, W. Peng and R. Alhadad, "Survey on SDN based network intrusion detection system using machine learning approaches", Peer-to-Peer Networking and Applications, vol. 12, no. 2, pp. 493-501, 2019.
- [8] M. Pradhan, C. K. Nayak and S. K. Pradhan, "Intrusion Detection System (IDS) and Their Types", Securing the Internet of Things: Concepts Methodologies Tools and Applications: IGI Global, pp. 481-497, 2020.
- [9] I. Firdausi, A. Erwin and A. S. Nugroho, "Analysis of machine learning techniques used in behavior-based malware detection", 2010 second international conference on advances in computing control and telecommunication technologies, pp. 201-203, 2010.
- [10] A. V. Joshi, Machine Learning and Artificial Intelligence, Springer, 2020.
- [11] Bishop, C. M. (2006). Pattern Recognition and Machine Learning. Springer.
- [12] Dua, D., & Graff, C. (2019). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. University of California, Irvine, School of Information and Computer Sciences.
- [13] Russom, P. (2011). Big Data Analytics. TDWI Best Practices Report.
- [14] Breiman, L. (2001). Random forests. Machine learning, 45(1), 5-32.
- [15] Géron, A. (2019). Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems. O'Reilly Media.
- [16] Moustafa, N., & Slay, J. (2016). The evaluation of Network Anomaly Detection Systems: Statistical analysis of the UNSW-NB15 data set and the comparison with the KDD99 data set. Information Security Journal: A Global Perspective, 25(1-3), 18-31.
- [17] Laskov, P., & Müller, K. R. (2005). Learning intrusion detection: supervised or unsupervised?. In International Symposium on Recent Advances in Intrusion Detection (pp. 50-72). Springer.
- [18] Chandola, V., Banerjee, A., & Kumar, V. (2009). Anomaly detection: A survey. ACM Computing Surveys (CSUR), 41(3), 1-58.
- [19] Natarajan, S., & Yi, S. (2014). A survey of intrusion detection systems leveraging machine learning techniques. Journal of Network and Computer Applications, 36(1), 42-57.
- [20] Sommer, R., & Paxson, V. (2010). Outside the closed world: On using machine learning for network intrusion detection. In 2010 IEEE symposium on security and privacy (pp. 305-316). IEEE.