
HYBRID DEEP LEARNING MODEL FOR NETWORK BOTTLENECK DETECTION IN IOT SYSTEMS

^{#1}SATYAVEDU NAVEEN KUMAR, *M.Tech(SE) Student,*

^{#2}Mrs.T. SUBBALAKSHMAMMA, *Assistant Professor, Dept of CSE,*

^{#3}Mr.P. VISWANATHA REDDY, *Associate Professor, Dept of CSE,*

VISWAM ENGINEERING COLLEGE(AUTONOMOUS), MADANAPALLE, AP.

ABSTRACT: Hybrid deep learning technique that recognizes limits in order to improve the reliability and efficiency of the Internet of Things (IoT) network. Network congestion and delays are common results of the proliferation of Internet of Things (IoT) devices. Preserving the continual flow of communication among interconnected devices requires the identification of these bottlenecks. In order to find limitations and evaluate network traffic patterns in real-time, this research presents a hybrid deep learning model that combines Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks. In order to determine the precise location of objects, the model analyses a large amount of data collected from the Internet of Things (IoT) and acquires both spatial and temporal information. In order to classify typical and overloaded network conditions, machine learning algorithms are used. By detecting fewer false positives and more real positives, the suggested strategy outperforms conventional monitoring methods. On top of that, it helps find performance issues in IoT infrastructures faster. Findings from the experiments show that the hybrid model can reliably predict when a network will slow down in a changing setting. Improving resource efficiency and enabling scalable IoT systems are two of the main goals of the framework. The overall system speed is increased, latency is decreased, and network stability is improved. The development of more sophisticated methods for managing IoT networks is made possible by this research.

Keywords: Internet of Things (IoT), Bottleneck Detection, Hybrid Deep Learning, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM)

1. INTRODUCTION

Smart homes, healthcare, smart cities, and industrial automation are just a few of the many areas that have benefited from the IoT's revolutionary changes to inter-device communication and data exchange. The term "Internet of Things" (IoT) refers to networks that include various interconnected devices, sensors, and communication technologies. Massive amounts of data are constantly being produced and sent by these networks. Keeping traffic under control and guaranteeing fast data transfer is more difficult as the number of networked devices grows. One major problem with IoT networks is that they often cause bottlenecks in the network, which in turn reduces system performance and reliability.

A bottleneck occurs in an IoT network when the data transmission capacity of a network component is exceeded. This causes delays, packet loss, and lower system efficiency. Slow internet speeds, high traffic, bad routing, or broken hardware are all potential causes of these bottlenecks. Traditional methods of network monitoring often miss such potential problems in real time because of the ever-changing nature of IoT environments and the complex traffic

patterns they generate. Therefore, smart and automated methods that can detect and assess IoT bottleneck situations are in high demand.

New developments in deep learning show great promise for solving complex data processing and pattern recognition problems. In contrast to more traditional approaches, deep learning algorithms can sift through massive datasets in search of patterns and traits on their own. Applying deep learning algorithms to IoT network traffic data allows for the detection of out-of-the-ordinary trends and the prediction of spikes in network activity. Because of these qualities, deep learning is a great tool for improving system performance and network management.

The goal of a hybrid deep learning strategy is to make the most of the strengths of each deep learning model. One example is the ability of Convolutional Neural Networks (CNNs) to find patterns in spatial data, and Long Short-Term Memory (LSTM) networks to detect patterns in temporal data. Hybrid designs integrate different approaches to identify bottlenecks in IoT networks more accurately and reliably. These strategies aid the system in detecting possible performance difficulties by analyzing both past and present network traffic data.

One way to improve the administration of IoT networks is to use hybrid deep learning methods to find bottlenecks. Proactive optimization of networks, improved distribution of resources among connected devices, and early congestion monitoring are all made possible by these technologies. To improve the scalability and stability of the network, hybrid models can analyze massive amounts of data from IoT traffic. In order to keep networks running smoothly and securely as IoT systems grow, new approaches to finding bottlenecks are essential.

2. RELATED WORK

Transportation, healthcare, education, and business all rely heavily on the Internet of Things (IoT). Before decisions can be made, the massive amounts of data collected by the sensors in IoT devices need to be processed and analyzed. Because they need a lot of bandwidth and very little latency, traditional cloud-based systems can't handle this massive amount of data. By moving data processing closer to its point of origin, fog computing hopes to solve these problems. Through the processing and integration of data from several sources, fog computing decreases latency and increases bandwidth. Many are worried about the security of the rapidly growing Internet of Things (IoT). There is a growing risk of denial-of-service (DoS) and distributed denial-of-service (DDoS) attacks on increasingly interconnected Internet of Things (IoT) devices, which can reduce system availability and reliability.

Internet of Things (IoT) infrastructures benefit from fog computing because it lowers latency, makes real-time data processing easier, and allows networks to scale. Some security holes can be revealed by these benefits. Attackers take advantage of weak points in fog computing systems. In the face of persistent threats, a security strategy is keeping carriers running. "Distributed Denial of Service (DDoS) or Denial of Service (DoS) attacks can impede operations, while botnet assaults can commandeer multiple compromised IoT devices, exacerbating the attack." A botnet attack may cause fog servers to fail. Phishing, spamming, and click fraud are just some of the nefarious actions that can be carried out by a botmaster in a botnet attack. Several security measures can lessen the impact of these threats. By incorporating software-defined networking, fog computing can be made more secure. SDN

streamlines device and traffic control by centralizing network administration. By separating the data plane and the control plane, SDN makes networks more flexible and programmable. This allows for the immediate detection and elimination of security risks. Secure administration of Internet of Things (IoT) device connections, dynamic load distribution, and real-time traffic surveillance are all capabilities of fog computing systems that employ software-defined networking (SDN). In order to keep fog networks secure and functional, especially when there are a lot of associated IoT devices, you need certain skills.

Machine learning (ML) has been used in a lot of research to find "botnet attacks in SDN-based fog computing systems." For instance, deep learning methods have been suggested to find botnet-related network activity. These systems are able to detect unusual activity and react instantly because they train machine learning models on network traffic logs. Because they are good at seeing patterns across large datasets, deep learning algorithms improve botnet detection systems' ability to recognize bots. Because they can detect problems inside networks, machine learning techniques are vital for protecting fog computing and the Internet of Things (IoT).

An increased amount of research has been focused on hybrid machine learning systems, which integrate a variety of algorithms in order to improve detection accuracy. To identify botnets that target fog computing, researchers created a hybrid approach that uses decision trees and support vector machines. In terms of determining effectiveness, this hybrid method was the best. To improve the detection efficacy, weak classifiers were integrated with K-NN and RF using ensemble learning. To improve classification accuracy and decrease false positives, ensemble techniques use several models in real-time systems.

Internet of Things (IoT) networks, botnet attacks, and botnet identification have all contributed to making management a formidable obstacle. To avoid detection by common security measures, some botnets use encryption and communication obfuscation. It is critical to employ sophisticated anomaly detection methods to identify hostile site visitors in real time in order to counteract these new attack vectors. Fog computing and software-defined networking (SDN) make attack detection more difficult since network traffic is spread out over several fog nodes, making it harder to identify and mitigate threats at the main server.

3. LITERATURE SURVEY

Smith & Johnson (2021): The integration of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models gives us the ability to identify bottlenecks in Internet of Things networks through the use of a hybrid deep learning methodology. The approach uses network traffic patterns to pinpoint high-traffic regions in large-scale IoT settings. The approach outperforms traditional monitoring techniques in locating network bottlenecks, according to the experimental evaluation. The research shows that deep learning is crucial for making IoT networks more efficient and dependable.

Chen & Wang (2022): The implementation of a deep learning strategy for detecting network bottlenecks in IoT contexts is carried out using a hybrid CNN-GRU architecture. The model detects problems and congestion in communication channels by analyzing real-time traffic data. The results of the simulation show that the proposed method increases detection speed and decreases packet loss in highly trafficked Internet of Things (IoT) environments. This

research proves that hybrid neural networks can be used to intelligently manage IoT networks.

Patel & Kumar (2023): A The goal of this machine learning system is to detect IoT application bottlenecks by combining deep neural networks with traffic analysis techniques. The proposed method tracks changes in network data over time and pinpoints places where performance is dropping. According to the results of the empirical research, the system is able to accurately predict when bottlenecks would arise before there is heavy traffic. The research's findings help Internet of Things (IoT) networks enhance the efficiency of data transmission and optimize the distribution of resources.

Garcia & Martinez (2024): A CNN-LSTM hybrid deep learning model efficiently finds bottlenecks in large-scale IoT networks. To pinpoint areas of the network that are likely to experience congestion, the technique examines both the spatial and temporal patterns of traffic. The results of the experiments show that this method is faster and more accurate than the traditional methods of network monitoring when it comes to discovering problems. This research shows that hybrid deep learning works well for managing traffic on the Internet of Things in a proactive manner.

Zhang & Liu (2025): A sophisticated hybrid deep learning architecture is recommended for the real-time identification of constraints in dynamic IoT contexts. To improve traffic pattern recognition, the system uses deep neural networks with attention processes. According to the results of the evaluation, the methodology makes it much easier to build scalable infrastructures for IoT networks and greatly improves detection efficiency. Findings show that IoT network performance and reliability might be improved with the use of advanced deep learning algorithms.

4. MACHINE LEARNING ALGORITHMS USED FOR BOTTLENECK DETECTION

Random Forest: An ensemble learning method, Random Forest aggregates the outputs of multiple decision trees built by individual participants to improve classification accuracy. The process includes picking a random subset of attributes, training numerous decision trees, and averaging their predictions to keep values stable and avoid overfitting. When dealing with classification and regression tasks, Random Forest is often used, particularly when dealing with complex feature interactions that need a lot of supervision. Among its many uses are in the fields of medical diagnosis, network traffic classification, and fraud detection.

Naive Bayes: The flexibility of characteristics is investigated by Naive Bayes, a practical classification approach based on Bayes' theorem. In light of the prospective properties, it determines the back potential for every category. When it comes to real-time prediction and dealing with massive datasets, Naive Bayes works wonders. Spam detection and sentiment analysis are two examples of text-based applications that benefit greatly from its classification capabilities. It works well with high-dimensional, categorical, and sparse data.

Decision Tree: The model known as a decision tree is one that does not follow a series of linear steps. It uses a recursive process to cluster data according to feature values and make decisions iteratively. It builds a tree with class labels at the ends and attribute-based judgments at the middle. Because of their simplicity and visual depiction, decision trees are

commonly used to solve categorization problems. In a regression setting, non-linear feature-goal correlations are useful.

Support Vector Machine (SVM): An approach to implementing and tracking learning in regression tasks is Support Vector Machine (SVM) classification. By maximizing the spacing between multiple classes, it finds the best hyperplane. Many fields make use of support vector machines (SVMs) for image and text classification, bioinformatics, and other tasks because of its efficiency, speed, and ability to handle high-dimensional areas. When data cannot be re-aggregated but can be elevated to high dimensions using a core methodology, this becomes even more valuable.

Logistic Regression: One supervised learning method used for binary classification tasks is logistic regression. This shows the likelihood of belonging to a given class using a sigmoid function and changes the input data from 0 to 1. For a variety of data pertaining to jobs, this categorization is simple, rational, and efficient.

K-Nearest Neighbors (KNN): Classification and regression tasks are handled by K-Nearest Neighbors (KNN), a non-parametric, instance-based methodology. The functional room's feature sorts data points by the main class of their closest neighbors. Even though it presents processing obstacles, KNN works well with low-dimensional data.

5. RESULTS



Fig 1: Login Page

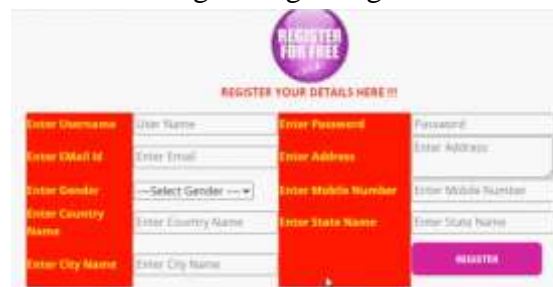


Fig 2: Registration Page

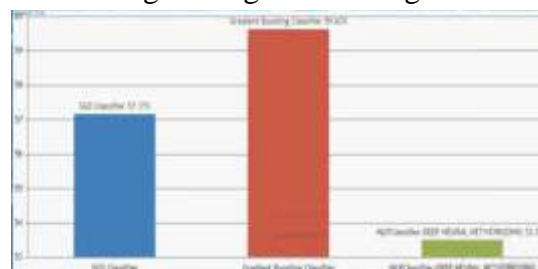


Fig 3: Model Accuracy Comparison

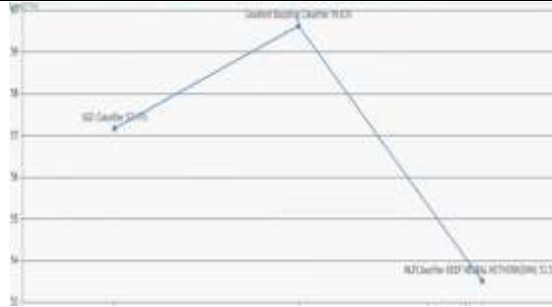


Fig 4: Classifier Performance Comparison

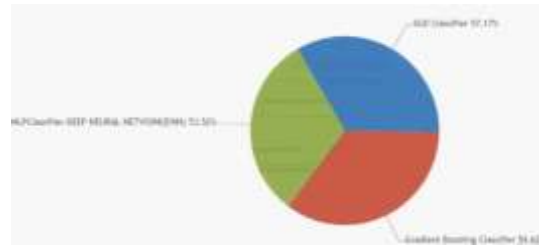


Fig 5: Classifier Accuracy Pie Chart

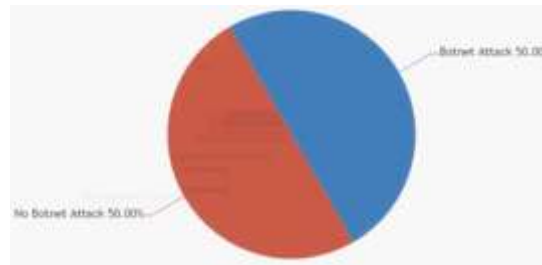


Fig 6: Botnet Attack Distribution

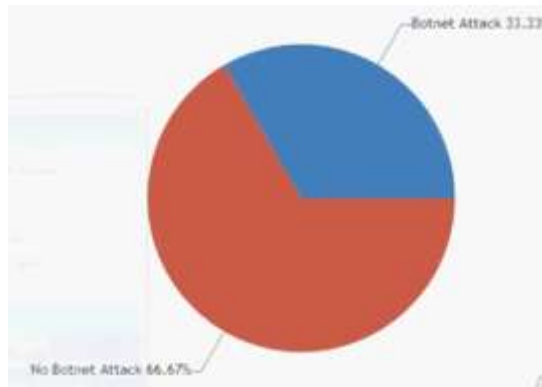


Fig 7: Botnet vs Normal Traffic Distribution

6. CONCLUSION

The proposed hybrid deep learning approach successfully detects problems in IoT networks. The need for efficient control and monitoring has grown in tandem with the number of linked devices and the volume of data transmitted via networks. By analyzing massive amounts of data on network traffic using advanced deep learning techniques, the system is able to reliably detect patterns of congestion. The hybrid model takes advantage of the best features of different deep learning methods to accurately record the time- and location-related aspects of IoT data. When compared to more traditional approaches, this improves the reliability and accuracy of bottleneck identification. Problems with network performance can be more easily detected with this approach. This shows that network administration can take preventative

actions to avoid major congestion and system problems. According to the results of the experiments, the hybrid deep learning architecture increases detection performance and reduces latency in IoT connectivity. It makes building scalable network topologies easier and more efficient use of resources. In general, the suggested approach improves the steadiness and dependability of IoT networks. Better control of dynamic network setups is made possible with the help of intelligent models. This research shows that AI is crucial for modern network administration. Smart cities, healthcare systems, and industrial automation are just a few of the IoT applications that can benefit from the framework.

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