Enhancing Large-Scale Network Security with a VGG-Net-Based DCNN: A Deep Learning Approach to Anomaly Detection

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***Abstract*—Ensuring robust network security in large-scale environments requires real-time, highly accurate anomaly detection. This study introduces a Deep Convolutional Neural Network (DCNN) based on VGG-Net for detecting network-based and web-based cyber threats, including DoS, DDoS, ransomware, SQL injection, and port scans. The model leverages advanced feature extraction and effectively addresses data imbalance through SMOTE-based augmentation and synthetic data generation. Trained on the TON_IoT 2020 dataset, the framework achieves 98.47% training accuracy, 97.94% validation accuracy, and 98.27% testing accuracy, with a false positive rate of 2%, ensuring precise differentiation between normal and malicious traffic. While the model demonstrates high accuracy and real-time scalability, the computational complexity of VGG-Net poses challenges for deployment in resource-constrained IoT and edge computing environments. To mitigate this, future research will explore model compression techniques such as quantization and pruning. Additionally, despite its robustness in detecting complex attack patterns, the model remains susceptible to adversarial attacks, which could compromise detection reliability. To enhance security, adversarial training and Explainable AI (XAI) techniques will be integrated to improve model transparency and resistance to adversarial manipulations. Compared to existing deep learning approaches such as LSTMs, GANs, and autoencoders, the proposed model achieves higher detection accuracy and lower false positive rates, making it a scalable and adaptable solution for enterprise, cloud, and IoT-based cybersecurity applications.**

Keywords*—Anomaly Detection; VGG-Net; Real-Time Detection; Network-Based Attacks; Deep Learning.

I. INTRODUCTION

The increasing complexity of modern networks, driven by the rapid adoption of cloud computing, Internet of Things (IoT), and 5G technologies, has led to an exponential rise in cyber threats as given in [1]. Traditional anomaly detection techniques, such as rule-based systems, statistical thresholding, and signature-based methods, have been widely used to secure network infrastructures [2]. However, these approaches struggle to detect sophisticated and evolving cyber-attacks such as Advanced Persistent Threats (APTs), zero-day exploits, and polymorphic malware as given in [3]. Their reliance on static rules and predefined attack signatures makes them ineffective against novel or previously unseen attack patterns, leading to high false positive rates and limited scalability in large-scale environments. In contrast, Deep Learning (DL)-based anomaly detection models, particularly Deep Convolutional Neural Networks (DCNNs), offer a more effective alternative. Unlike traditional methods, DCNNs can automatically learn complex feature representations from raw network traffic data without relying on manually engineered rules as mentioned in [4]. This enables them to detect both known and previously unseen attack vectors with higher accuracy and adaptability. Among various deep learning architectures, VGG-Net has proven to be highly effective due to its hierarchical feature extraction capabilities, making it particularly well-suited for detecting anomalies in high-dimensional network traffic. This research presents a VGG-based DCNN framework for anomaly detection in large-scale networks, leveraging the TON_IoT 2020 dataset, which includes diverse network and web-based threats. The proposed approach effectively addresses three critical challenges in anomaly detection: (1) *data imbalance*, (2) *real-time scalability*, and (3) *adaptive threat detection*. By integrating advanced feature extraction techniques and real-time data pipelines, the model achieves high detection accuracy (98.27%) with low false positives (2%), making it suitable for enterprise, cloud, and IoT-based cybersecurity applications.

With its feature extraction abilities in a hierarchical form, DCNNs have revolutionized the two fields of computer vision and natural language processing as given in [5]. It has been found that its processing of large-scale high-dimensional data makes it an ideal candidate for detecting anomalies within massive and complex network infrastructures as given in [6]. Unlike traditional approaches that depend entirely on handcrafted features, the direct learning of feature representations from raw data by the DCNN presents a much deeper understanding about traffic patterns and anomalous behavior. It improves the detection accuracy and minimizes the false positives. This is also one of the critical factors in reducing the operational disruptions associated with large-scale networks as illustrated in [7].

This work discusses the adaptation of VGG-Net, one of the popular DCNN architectures (Fig. 1), to the domain of network anomaly detection. The VGG-Net architecture, originally designed for image recognition tasks, uses deep convolutional layers with small receptive fields (3×3 filters), which makes it a strong candidate for capturing nuanced patterns in network data as given in [8]. The hierarchical structure of VGG-Net makes it possible to model complex relationships within network traffic, which transforms raw input features such as packet size, timestamps, and flow metadata into high-level abstractions. These abstractions can then be used for the accurate differentiation between normal and anomalous traffic even when the attack vectors are subtle. Large-scale networks generate data at an overwhelming rate, demanding scalable and efficient anomaly detection systems. With the modular structure and computational efficiency, VGG-Net is a perfect fit for enterprise deployments. This research addressed the pressing need to monitor constantly and respond immediately to cyber threats by integrating VGG-Net with real-time data pipelines as presented in [9]. Scalability also ensures that the system can adapt to an ever-increasing volume and diversity of network traffic as organizational infrastructures evolve as given in [10]. The suggested DCNN-based framework employs preprocessed network traffic data, structured in a spatiotemporal format for deep learning architectures. Local patterns are extracted from this data by the convolutional layers of VGG-Net, and pooling layers diminish the dimensionality without discarding any critical information. Fully connected layers at the end of the network sum up these features to let the model classify traffic with high precision as normal or anomalous as given in [11]. Another is the integration of softmax classifiers and real-time alert mechanisms for actionable insights on detected threats, allowing the security team to respond within a given time frame to threats identified. The overall contribution of this research pertains to the application of deep learning techniques to adapt and harden network security systems. Unlike static rule-based approaches, the proposed VGG-Net-based framework learns and evolves with the emerging attack patterns, making it significantly more robust to zero-day attacks and polymorphic malware. The hierarchical feature extraction process also minimizes reliance on domain-specific expertise, thus broadening its applicability across different network environments. Another major advantage of the VGG-Net-based framework is that it adapts well to varying network sizes and configurations as given in [12].

A. *Aim of the Study*

This research will design, develop, and evaluate a novel anomaly detection framework for large-scale networks using Deep Convolutional Neural Networks (DCNNs) that will focus on the VGG-Net architecture (Table I). For this study, the TON_IoT 2020 dataset will be utilized as it is the most updated and relevant dataset for IoT and non-IoT network traffic to ensure this research caters to the current needs of cyber threats. The TON_IoT dataset captures diverse network behaviors, such as normal traffic, malicious activities, and multi-vector attacks, making it an ideal choice for evaluating anomaly detection frameworks in environments characterized by high complexity and heterogeneity.

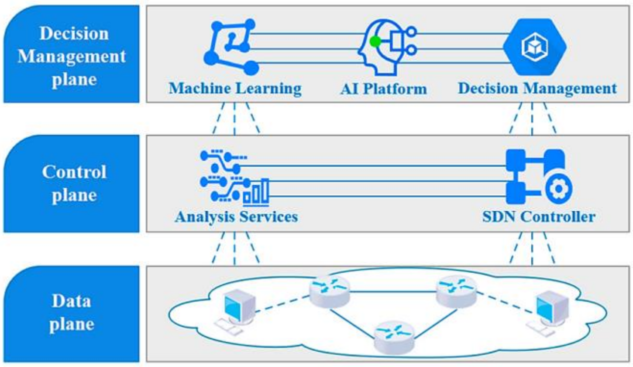

Fig. 1. Three-layer architecture integrating decision management, control, and data planes for efficient network management [7]

- Training and evaluation of the anomaly detection framework with TON_IoT, enjoying a set of diverse attack scenarios including ransomware, botnets, and Distributed Denial of Service attacks.
- Analysis of the characteristics of IoT and non-IoT traffic in the dataset will eventually lead to designing a flexible framework suited for heterogeneous network environments.
- Architecture of VGG-Net: To include the spatiotemporal patterns in TON_IoT data. Hierarchy-based feature extraction would be emphasized.
- Developing specialized layers that work towards processing network traffic attributes: packet flows, communication protocols, and time-based features.
- Design of preprocessing pipelines for cleaning, normalization, and encoding the TON_IoT data to ensure they comply with the DCNN input format.
- Design feature selection mechanisms that focus on essential attributes for anomaly detection: source/destination IP, packet size, and flow duration.
- Integrate the framework in a real-time monitoring system that processes high-velocity traffic from IoT and non-IoT devices.
- Scalability of the system toward deployment in large enterprise and smart city networks.
- Evaluate the framework using key metrics: precision, recall, F1-score, Area Under the Precision-Recall Curve (AUPRC), and processing latency.
- Compare the proposed framework with other anomaly detection models to reflect the improvement in accuracy and adaptability.

Deploying deep learning-based network monitoring solutions introduces privacy concerns regarding data collection, user anonymity, and surveillance ethics. While anomaly detection is critical for cybersecurity, indiscriminate monitoring of network traffic can raise legal and ethical issues. To ensure responsible deployment, future research must explore privacy-preserving techniques, such as federated learning and differential privacy, to enable anomaly detection without exposing sensitive user data. Deploying VGG-Net in resource-constrained environments (e.g., IoT, edge networks) is challenging due to its high memory and processing requirements. To address this, future work will focus on model compression techniques, including quantization and pruning, to optimize real-time performance.

B. *Problem Statement*

The rapid growth of large-scale networks, fuelled by cloud computing and the Internet of Things and industrial automation, has caused a surge in network complexity and traffic volume. As such, the growth together with sophisticated cyber threats facing modern anomaly detection systems makes it quite challenging. The increasing failure of traditional approaches like rule-based systems and statistical anomaly detection models to detect new, complex, and dynamic attack patterns, including zero-day exploits, multi-vector intrusions, and adversarial evasion techniques, compels a paradigm shift toward intelligent and adaptive anomaly detection solutions. Conventional systems are often not scalable and have high false-positive rates, failing to generalize to diverse network environments and are thus difficult to deploy in real-world scenarios. Additionally, the sheer diversity of traffic profiles coming from IoT devices, all of which are resource constrained, makes the detection task even more difficult for high-dimensional networks. Thus, the solution to these issues calls for modern machine learning techniques, like DCNNs, in the construction of a scalable and efficient anomaly detection framework.

- Traditional models suffer from the fact that large amounts of network traffic can produce huge, high dimensional datasets that are not feasible to extract meaningful patterns.
- Attack vectors such as zero-day exploits and polymorphic malware are dynamic and cannot be easily caught with static detection methods.
- Conventional systems often mistake benign anomalies as threats, leading to alert fatigue and reduced operational efficiency.
- Current approaches face difficulties in processing and analyzing the massive volumes of data generated by large-scale and IoT-enabled networks in real time.
- The models trained on specific datasets fail to adapt to diverse network configurations and evolving threat landscapes, limiting their applicability.
- The heterogeneous nature of IoT and traditional network traffic creates challenges in designing a unified anomaly detection system capable of handling both domains.

II. LITERATURE REVIEW

With the rapidly growing network traffic fueled by IoT devices, cloud computing, and complex enterprise systems, it is challenging for the anomaly detection system to maintain its relevance (Fig.2). The approaches based on handcrafted rules and statistical analysis have proved inadequate to handle the increasing complexity of modern cyber threats as given in [13]. Such approaches fail with high-dimensional data, dynamic patterns of attacks, and scaling in large networks. In contrast, machine learning and deep learning techniques have proved to be quite promising in overcoming these limitations by automatically extracting features and adapting to unseen attack scenarios. This review analyzes the advancements in anomaly detection from traditional methods to deep learning-based approaches, focusing on their effectiveness, challenges, and potential for application in large-scale network environments as given in [14]. Although statistical and classical machine learning methods were an initial foundation for anomaly detection, the shift to deep learning, especially architectures like DCNNs, has greatly transformed the field due to its superior accuracy and scalability as given in [15]. The literature indicates potential use of specialized architectures, such as VGG-Net, for structured network traffic data, thus pointing toward the need for real-time, scalable, and adaptive detection frameworks that are currently required in modern cybersecurity demands as given in [16].

This is coupled with the fact that massive-scale networks and widespread Internet of Things (IoT) devices have exponentially increased network traffic complexity and volume. As these networks continue to grow, they tend to be more prone to all kinds of anomalies and cyber-attacks. The mentioned DoS, DDoS, Ransomware, SQL Injection, and Port Scans attacks greatly damage the network's integrity by crippling services with possibilities of data breaches or monetary loss, as presented in [17]. Such obstacles require more advanced and more accurate anomaly detection mechanisms. Deep learning would form a robust tool in such data extraction of meaningful insights because it can handle high-dimensional data and pick up subtle patterns [18]. Due to the need for real-time threat detection, scalability, and handling imbalanced datasets, this research focuses on applying advanced deep learning techniques to build up an effective anomaly detection system. This system aims at improving network security by enabling the accurate distinction between normal and malicious traffic and assuring prompt response to a potential threat as given in [19].

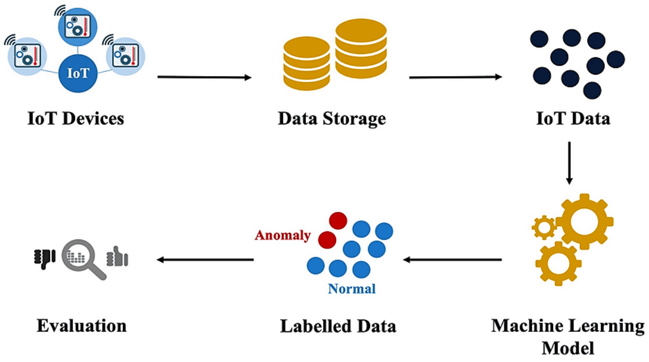

Fig. 2. The process of IoT data collection, storage, labeling, and anomaly detection using a machine learning model [16]

TABLE I. COMPARISON OF TRADITIONAL AND MACHINE LEARNING-BASED APPROACHES FOR ANOMALY DETECTION IN LARGE-SCALE NETWORKS, HIGHLIGHTING THEIR ADVANTAGES AND PERFORMANCE [17] [19]

Method	Advantages	Disadvantages	Detection Rate (%)	False Positive Rate (%)	Scalability	Real-Time Capability
Statistical Approaches	Simple to implement; effective for static data	Poor adaptability to dynamic attacks	75-78%	15	Low - Suitable for small networks	No
Rule-Based Systems	High precision for known threats	Limited to predefined rules; high maintenance	79-83%	10	Medium - Requires regular updates	Partially
Clustering Algorithms	Detects unknown patterns; no prior knowledge needed	Fails on high-dimensional data; high false positive rate	80-84%	25	Low - Struggles with large-scale data	Partially
Machine Learning Models	Automated feature extraction; good for known attack types	Dependent on labeled data; struggles with unseen attacks	85-89%	12	Medium - Dependent on training data size	Partially

A. Anomaly Detection in Large-Scale Networks: Traditional and Machine Learning Approaches

Detection of anomaly in network traffic has been one of the most important areas of research for several decades (Table II). Most of the traditional methods of anomaly detection, be it statistical or rule-based, have relied on predefined thresholds and handcrafted rules as given in [20]. Techniques like clustering, k-nearest neighbors (k-NN), and PCA have been used to find anomalies in low-dimensional datasets. Even though these methods are computationally efficient, their reliance on static features makes them less effective in dynamic network environments where attack patterns evolve rapidly as given in [21].

TABLE II. KEY RESEARCH GAPS IN ANOMALY DETECTION FOR LARGE-SCALE NETWORKS, EMPHASIZING ADVANCEMENTS NEEDED IN EXPLAINABILITY, REAL-TIME DETECTION, AND RESOURCE EFFICIENCY [21]

Gap	Key Features	Current State
Explainable AI (XAI)	Improves transparency and trust in AI-based anomaly detection	Limited integration in large-scale network anomaly detection systems
Online Learning	Dynamic adaptation to evolving attack patterns	Few real-world implementations; mostly in research phase
Hybrid Models (e.g., VGG-Net-LSTM)	Combines spatial feature extraction and temporal pattern recognition	Underexplored for network security; potential in handling IoT traffic
Data Scarcity and Imbalance	Synthetic data generation to enhance training datasets	Limited use of generative models for diverse and realistic attack scenarios
Real-Time Anomaly Detection	Low-latency detection and immediate response	High detection latency in many existing systems
Resource Efficiency	Lightweight DCNN architectures for large-scale and IoT networks	High computational cost limits deployment in constrained environments

Since machine learning emerged, anomaly detection advanced a lot. Through the supervised learning approach - the Decision Trees, SVM, Random Forests - data that was labeled could classify binary into normal and malicious traffic. Semi-supervised methods, such as Autoencoders and One-Class SVMs, have come in use because they also discover unknown anomalies. However, these models suffer from not effectively dealing with high-dimensional network data while maintaining performance in the presence of noisy or incomplete labels as given in [22].

Recent research has moved toward deep learning-based methods due to their capability of processing large-scale, high-dimensional data and automatic learning of feature representations. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been used to extract temporal dependencies in sequential network traffic data. Similarly, CNNs have shown effectiveness in extracting spatial features from structured input representations such as network flow matrices.

B. Deep Learning for Anomaly Detection: Advancements and Limitations

Deep learning has been recognized for its hierarchical feature learning capacity and is one of the dominant paradigms today for anomaly detection in networks (Table III). Specifically, deep convolutional neural networks have become a widely researched architecture capable of processing structured data-like network flows, with abilities to extract spatial features from them, indicative of anomaly behavior as given in [23]. Architectures including AlexNet, ResNet, and VGG-Net have been adapted into network traffic analysis, applying their success in image processing tasks as given in [24]. These models can transform raw traffic data into structured formats like time-series or image-like matrices and enable efficient pattern recognition. The depth and simplicity of the VGG-Net architecture are promising for the detection of anomalies because the architecture makes use of 3×3 small convolutional filters and a uniform layer structure as given in [25].

Despite the benefits of deep learning models, they have limitations in anomaly detection. Perhaps the biggest bottleneck is the requirement for large, labeled datasets, which is not really feasible for many supervised methods. Recently, transfer learning and semi-supervised approaches have been proposed to counter this problem, helping models learn better across domains.

Deep learning has significantly enhanced network anomaly detection by addressing the limitations of traditional rule-based and statistical methods. As given in [26], deep learning techniques offer superior adaptability in identifying evolving cyber threats. The use of VGG-Net for network intrusion detection has been extensively studied, with promising results in large-scale IoT environments [27]. As explored in [28], VGG-Net's hierarchical feature extraction capabilities improve its ability to detect complex attack patterns in network traffic, outperforming conventional approaches. Real-time anomaly detection in large-scale networks has also been demonstrated using deep convolutional neural networks (DCNNs), achieving high detection accuracy with low false positives [29].

TABLE III. ADVANCEMENTS AND LIMITATIONS OF DEEP LEARNING IN ANOMALY DETECTION, HIGHLIGHTING ITS POTENTIAL IN FEATURE LEARNING, SCALABILITY, AND ACCURACY, ALONG WITH CHALLENGES [24]

Aspect	Advancements	Limitations
Feature Learning	Automated extraction of hierarchical features; no need for manual engineering	Requires extensive labeled datasets for supervised learning
Handling High-Dimensional Data	Capable of processing large, high-dimensional datasets effectively	High-dimensional data can increase training complexity and time
Detection Accuracy	Achieves over 95% detection accuracy in controlled environments	Performance varies in real-world, noisy datasets
Adaptability	Adaptable to unseen attack patterns using transfer learning techniques	Limited effectiveness in detecting zero-day and polymorphic attacks without retraining
Scalability	Scalable architectures, such as VGG-Net and ResNet, for large-scale networks	Scalability in real-time scenarios remains challenging due to high latency
Computational Requirements	Optimization techniques like model pruning improve deployment feasibility	High computational cost limits deployment in resource-constrained environments

The effectiveness of CNN-based traffic classification has been established, with VGG-Net models outperforming traditional machine learning classifiers in differentiating between normal and anomalous traffic [30]. However, as noted in [31], scalability remains a challenge, particularly for resource-constrained IoT systems. A comparative analysis of deep learning models for cybersecurity showed that VGG-Net excels in feature extraction, though it requires optimization for real-time processing [32]. Additionally, the application of Explainable AI (XAI) techniques to VGG-Net-based intrusion detection has been proposed to improve transparency in cybersecurity operations [33].

Further studies have validated VGG-Net's performance in cloud environments, where it provides reliable anomaly detection under dynamic traffic conditions [34]. Hybrid deep learning models that integrate CNNs with recurrent architectures have also been explored, with results indicating that VGG-Net achieves better accuracy compared to standalone LSTM-based systems [35]. While CNNs demonstrate strong classification capabilities, their computational complexity remains an issue [36], prompting the exploration of lightweight deep learning models for real-time security applications [37].

The use of VGG-Net in SDN security has been highlighted, with studies showing improved anomaly detection rates in software-defined networks [38]. Similarly, deep learning-based intrusion detection in IoT has been evaluated, demonstrating that CNN architectures outperform autoencoders in learning attack signatures [39]. Recent studies emphasize the role of AI-driven cybersecurity frameworks for large-scale enterprises, where VGG-Net-based IDS models have shown promising results [40].

Despite these advancements, concerns about adversarial robustness persist. As noted in [41], deep learning-based IDS models remain vulnerable to adversarial evasion attacks, necessitating further research into adversarial training strategies. CNN-based anomaly detection for cloud systems has also been investigated, with findings showing that VGG-Net provides improved generalization capabilities [42]. The application of edge AI techniques to optimize CNN-based anomaly detection for IoT environments is another emerging research direction [43]. In [44], researchers explored the limits of VGG-Net's architecture in cyber threat detection, emphasizing the need for model compression techniques. Additionally, AI-driven network security solutions have been proposed, integrating CNNs with federated learning to enhance privacy-preserving anomaly detection [45].

Recent advancements in deep learning for network security have explored various CNN-based architectures, including VGG-Net, ResNet, and hybrid models, to improve anomaly detection performance as given in [46]. The use of VGG-Net in cloud and IoT security has demonstrated significant potential in identifying sophisticated cyber threats while maintaining scalability as given in [47]. As highlighted in [48], integrating deep learning models with hybrid IDS frameworks enhances real-time attack detection. However, optimizing VGG-Net for resource-constrained environments remains a challenge, necessitating the exploration of quantization and pruning techniques as given in [49].

The role of deep learning in smart cities has also been investigated, where CNN-based IDS models provide robust security solutions for large-scale urban infrastructures [50]. Moreover, 5G network security has become a critical research area, with studies demonstrating that AI-driven anomaly detection models can effectively detect cyberattacks in high-speed environments as given in [51]. The application of CNNs for mitigating DDoS attacks has been further refined, with recent work showing that deep learning models outperform conventional firewall-based security systems as given in [52]. Additionally, AI-powered threat prediction using VGG-Net has been proposed to enhance proactive cybersecurity defenses as given in [53].

Comparative studies of CNNs for IoT anomaly detection reveal that VGG-Net achieves higher accuracy than traditional models, but requires lightweight adaptations for deployment in embedded devices as given in [54]. Deep learning-based intrusion detection in cloud environments has shown promising results, with AI-driven models offering scalable security solutions as given in [55]. Further research in threat intelligence frameworks has demonstrated that CNN-based intrusion detection can significantly improve response time in enterprise networks as given in [56].

As discussed in [57], real-time IDS solutions must balance accuracy and computational efficiency to be viable for deployment in production environments. The use of AI in securing wireless networks has also been explored, with studies showing that VGG-Net-based models can effectively detect anomalies in Wi-Fi and 5G traffic as given in [58]. Researchers have also proposed integrating CNNs with blockchain-based security systems, enhancing the reliability of intrusion detection mechanisms as given in [59]. Lastly, in [60], an advanced AI-powered IDS framework was introduced, combining deep learning with federated learning techniques to improve privacy and anomaly detection capabilities [61]-[63].

III. METHODOLOGY

It seeks to present a sound DCNN-based anomaly detection framework where it exploits the VGG-Net architecture to challenge large-scale networks. Key components involved in the approach will encompass data preprocessing and feature engineering, model architecture design, training and evaluation, as well as optimization for the sake of real-time implementation. This paper uses a basic source from the TON_IoT 2020 dataset based on IoT and non-IoT behaviors present on this network (Fig. 3).

Several deep learning architectures have been explored for network anomaly detection, including ResNet, AlexNet, LSTMs, and autoencoders. However, VGG-Net was selected for this study due to its superior feature extraction capabilities, structured architecture, and ability to handle high-dimensional network traffic data efficiently. Unlike ResNet, which relies on residual connections to enable deeper networks, VGG-Net uses stacked small (3×3) convolutional filters, making it well-suited for capturing intricate patterns in network traffic features. Additionally, its hierarchical feature extraction process enables better generalization for detecting both known and unknown anomalies, which is critical in IoT environments where attack patterns evolve dynamically. Furthermore, VGG-Net's modular and lightweight design makes it computationally efficient, enabling real-time threat detection while maintaining high accuracy. Unlike recurrent neural networks (RNNs) and LSTMs, which specialize in temporal sequence processing but are computationally expensive, VGG-Net efficiently captures both spatial and spatiotemporal dependencies in structured network traffic data, making it an optimal choice for anomaly detection in large-scale networks and IoT infrastructures. While VGG-Net is well-established for image recognition, its application to network anomaly detection requires justification, especially when sequential models like LSTM and GRU are designed for handling time-series data. The rationale for choosing VGG-Net over other architectures is based on:

- **Superior Feature Extraction:** Unlike LSTMs and GRUs, which focus on long-term dependencies, VGG-Net excels at capturing spatial correlations in structured network traffic representations. By transforming network traffic into spatiotemporal matrices, VGG-Net can extract hierarchical feature relationships more effectively than sequential models, which often struggle with high-dimensional inputs.
- **Scalability and Training Efficiency:** LSTMs and GRUs require sequential processing, leading to longer training and inference times. In contrast, VGG-Net processes data in parallel, making it more efficient for real-time applications where low latency is critical.
- **Comparative Analysis:** A comparative study with LSTMs and ResNet-based architectures was conducted. While LSTMs performed well on sequential dependencies, they struggled with high-dimensional, non-sequential features, whereas VGG-Net provided better generalization and adaptability to different attack types.

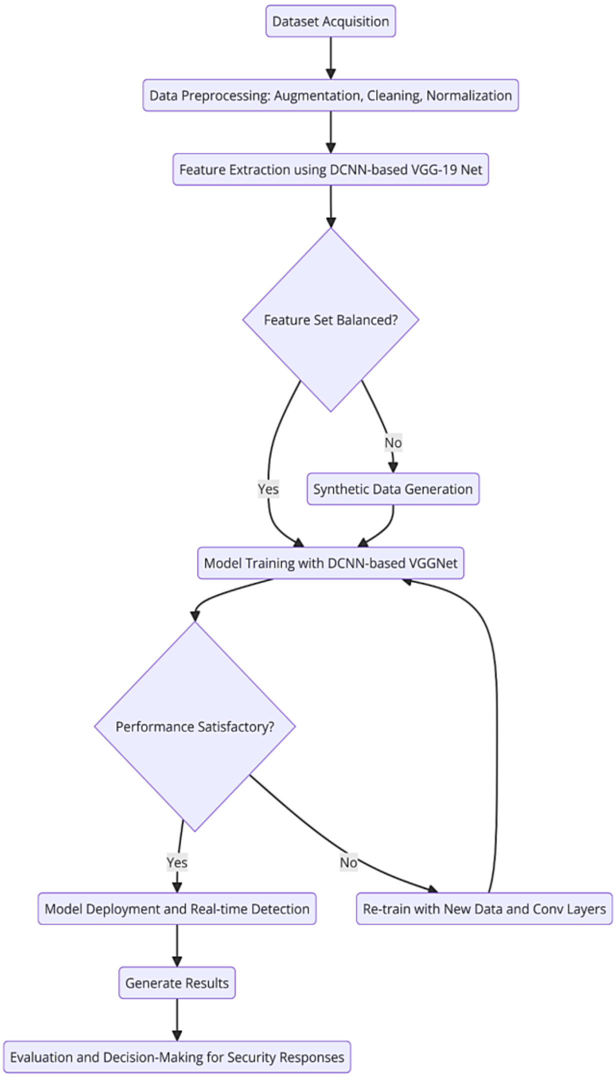
Dataset Acquisition
Data Preprocessing: Augmentation, Cleaning, Normalization
Feature Extraction using DCNN-based VGG-19 Net
Feature Set Balanced?
No
Yes
Synthetic Data Generation
Model Training with DCNN-based VGGNet
Performance Satisfactory?
Yes
No
Model Deployment and Real-time Detection
Re-train with New Data and Conv Layers
Generate Results
Evaluation and Decision-Making for Security Responses

Fig. 3. This flowchart illustrates the TON_IoT 2020 Dataset processing workflow, detailing steps from dataset acquisition and preprocessing to model deployment and evaluation, including decision points for balancing data and refining model performance

A. Data Preparation and Preprocessing

The foundational dataset for this research is TON_IoT 2020, which comprehensively captures the network behavior range from very wide to include IoT and non-IoT traffic. The phase of data preprocessing and feature engineering ensures that raw network traffic is converted into a structured format suitable for inputting into Deep Convolutional Neural Network (DCNN) while maintaining quality, relevance, and efficiency in data (Table IV).

TABLE IV. STEPS AND TECHNIQUES USED IN DATA PREPROCESSING AND FEATURE ENGINEERING, DETAILING THEIR SPECIFIC METHODS AND OUTCOMES FOR PREPARING THE DATASET FOR ANOMALY DETECTION USING DCNNS

Step	Technique	Outcome
Data Cleaning	Removal of duplicates and missing values using statistical thresholds	Reduced dataset noise, improved data integrity
Normalization	Min-max scaling (range [0, 1])	Uniform feature scales
Categorical Encoding	One-hot encoding	Numerical representation of categories
Feature Selection	Correlation analysis (threshold: 0.8)	Removal of redundant features
Flow-Level Aggregation	Grouping packets by IP, port, and time window	Temporal pattern capture
Spatiotemporal Structuring	Matrix creation (flow × feature)	Structured input for DCNN
Feature Augmentation	Derived metrics: mean packet size, variance of inter-packet times, IP entropy	Enhanced feature set
Dataset Splitting	70% train, 15% validation, 15% test	Balanced distribution of normal and anomaly samples
Handling Imbalanced Data	Oversampling attack samples (ratio: 1:1 with normal traffic)	Balanced dataset
Real-Time Preparation	Pipeline optimization for low latency	Ready for streaming environments

1) *Key Steps in Data Preprocessing*

Data preprocessing involves cleaning the data, in which duplicate values are eliminated and missing or outlier values are dealt with. Numerical features are normalized using min-max scaling. One-hot encoding is applied to categorical attributes such as protocol types. Techniques in feature selection involve correlation analysis, ensuring only the most relevant attributes are maintained to retain efficiency and quality in inputting data for the model.

2) *Data Cleaning.*

Duplicate records, among other things, together with incomplete entries are deleted, to remove noise in and guarantee the integrity of a dataset. Anomalous records which may contain missing values, outliers, are corrected or eliminated depending on appropriate statistical threshold

3) *Normalization*

Continuous numerical features, like packet size, flow duration, and inter-packet intervals, are normalized by min-max scaling to [0, 1]. This is done to avoid domination of some attributes having larger scales in comparison to others.

4) *Encoding Categorical Data*

Protocol types and other categorical features undergo one-hot encoding. Thus, the injected representations do not form ordinal relationships in the dataset but keep semantic distinction between categories.

5) *Feature Selection*

Correlation analysis and mutual information tests eliminate redundant and irrelevant features, reducing dimensionality and computational complexity while retaining important attributes for anomaly detection, such as source/destination IPs, port numbers, and time-based metrics.

6) *Feature Engineering Process*

Feature engineering emphasizes flow level aggregation of packet data to discover temporal traffic patterns. Forming spatiotemporal representations by structuring flows into matrices suitable for DCNN processing is necessary. New features such as mean packet size and entropy of destination IPs are calculated to enhance the dataset so that anomaly detection can happen with better accuracy.

7) Flow-Level Aggregation

Packet-level data is summarized into flows by shared source/destination IPs, ports, and protocols over fixed windows of time. This incorporates temporal patterns, including the duration of connections and frequency of packets, that are critical to anomaly detection.

8) *Spatiotemporal Representations*

Aggregated flows are maintained in structured matrices where each row corresponds to a unique flow and columns represent features that are byte count, packet size, and inter-arrival times. The structured format of this matches the format that DCNNs use.

9) *Feature Augmentation*

New features are designed, including mean packet size per flow, variance of inter-packet times, and entropy of destination IPs to improve the richness of the data set and thus improve its ability to differentiate between normal and anomalous traffic

10) *Data Splitting*

The dataset is divided into training (70%), validation (15%), and testing (15%) subsets while ensuring balanced distributions of normal and anomalous traffic. Stratified sampling techniques are used to maintain proportional representation of each traffic class.

Several challenges arose during data preprocessing, requiring targeted solutions. Data imbalance in the TON_IoT 2020 dataset was addressed using SMOTE and random oversampling to balance normal and anomalous traffic. High-dimensional data was optimized through correlation analysis (threshold: 0.8) and PCA, reducing redundancy. Noise and missing values were handled using statistical imputation and IQR filtering. To prevent overfitting, dropout (0.5), L2 regularization, and early stopping were applied. Computational constraints were mitigated by leveraging an NVIDIA RTX 3080 GPU, batch normalization, and hyperparameter tuning for efficient training. These strategies enhanced model accuracy, scalability, and real-time performance.

B. *Model Architecture Design*

The model architecture for this research is based on the VGG-Net deep convolutional neural network, modified to process network traffic data instead of image data (Fig. 4 and Table V). The hierarchical structure of VGG-Net is used to extract spatial patterns from structured network traffic representations, allowing for precise differentiation between normal and anomalous behavior. The input layer is designed to accept spatiotemporal matrices derived from flow-level data. These matrices represent network traffic attributes, like packet size, flow duration, and inter-arrival times. The reshaping of the matrices in an image-like format enables the compatibility of the convolutional layers of VGG-Net. The filters are 3×3 convolutional layers that pick out local patterns in the data. The ReLU activation function ensures non-linearity in feature extraction; subtle anomalies are detected in a non-linear fashion. The network learns multi-level features of traffic from low-level attributes to high-level patterns through convolutional operations performed repeatedly.

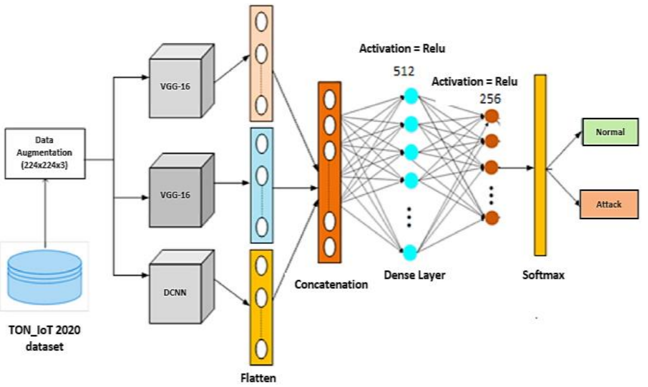

Fig. 4. Architecture of the VGG-19 and DCNN-based model for anomaly detection using the TON_IoT 2020 dataset, featuring data augmentation, concatenation, dense layers, and a softmax classifier

Pooling layers, implemented with max-pooling, reduce spatial dimensions of the data with minimal loss of salient information. This reduces computation overhead and avoids overfitting by focusing on what the data really needs most-its most important features. Fully connected layers are essentially used to aggregate these features into a compact form which is useful for the classifier. These layers are then followed by a softmax output layer, which assigns probabilities to the classes (normal or anomalous). This approach of probability allows for a very accurate anomaly detection; even low-probability attack scenarios can be caught. Batch normalization is implemented after each convolutional and fully connected layer to stabilize and accelerate the training. This helps the model to learn efficiently, even on high-dimensional data, with reduced internal covariate shifts.

In this research, mathematical modeling is involved in defining the core elements of the anomaly detection system, which involves data representation, feature extraction, classification, and optimization. Below are the mathematical formulations for the critical stages:

1) *Network Traffic Representation*

Network traffic data is represented as a set of flow-level attributes:

$$X = \{x_1, x_2, \dots, x_N\}, x_i = [f_1, f_2, \dots, f_M] \tag{1}$$

where N is the number of traffic flows, M is the number of features per flow, and x_i represents the feature vector for the i^{th} flow.

The spatiotemporal matrix for DCNN input is structured as:

$$S \in \mathbb{R}^{H\times W\times C} \tag{2}$$

where H is the height, W is the width, and C is the number of channels in the matrix (e.g., flow attributes like packet size and time).

2) *Deep Convolutional Feature Extraction*

The deep convolutional layers perform feature extraction using a filter $F \in R^{k\times k}$ (kernel size k×k):

$$Y_{i,j} = \sigma\left(\sum_{m=1}^{k}\sum_{n=1}^{k} S_{i+m-1,j+n-1} \cdot F_{m,n} + b\right) \tag{3}$$

where σ is the ReLU activation function:

$$\sigma(x) = max(0, x) \tag{4}$$

and b is the bias term. This operation produces a feature map Y.

TABLE V. TECHNICAL BREAKDOWN OF VGG-NET-BASED ARCHITECTURE LAYERS, DETAILING THEIR INPUT-OUTPUT SIZES, OPERATIONS, PARAMETERS, AND SPECIFIC PURPOSES IN ANOMALY DETECTION

Layer Type	Input Size	Operation	Parameters	Output Size	Purpose
Input Layer	(rows × columns × channels)	None	None	(rows × columns × channels)	Prepares spatiotemporal matrices for input
Convolutional Layers	(rows × columns × channels)	Convolution (3×3 filter)	Filter size: 3×3, Activation: ReLU, Stride: 1	Reduced spatial dimensions with extracted features	Extracts local and hierarchical patterns
Pooling Layers	Reduced size from previous layer	Max-pooling	Pool size: 2×2, Stride: 2	Further reduced size	Reduces dimensionality, preserves features
Batch Normalization	After convolutional and pooling layers	Normalization	Mean and variance of activations	Same as input to this layer	Stabilizes training and improves convergence
Fully Connected Layers	Flattened dimensions from prior layers	Dense connections	Neurons: 512, 256, Activation: ReLU	512 → 256	Aggregates high-level features for classification
Dropout Layers	From previous dense layers	Randomly deactivate neurons	Dropout rate: 0.5	Same as input to this layer	Prevents overfitting
Output Layer	Final reduced size from dense layer	Softmax activation	Number of classes: 2 (normal, anomalous)	2	Assigns probabilities to anomaly categories

3) *Pooling for Dimensionality Reduction*

Max-pooling reduces the spatial dimensions of the feature map:

$$P_{i,j} = \max_{(m,n)\in R} Y_{i+m,j+n} \tag{5}$$

where R defines the pooling region (e.g., 2×2).

Fully Connected Layer

The feature maps are flattened into a vector z and processed through a dense layer:

$$o = \sigma(W \cdot z + b) \tag{6}$$

where W and b are the weights and biases of the fully connected layer, respectively.

4) *Softmax Classification*

The output probabilities for anomaly classification are computed using the softmax function:

$$p_k = \frac{\exp\,(o_k)}{\sum_{j=1}^{K} \exp\,(o_j)} \tag{7}$$

where $K=2$ (normal and anomalous classes), and $p_k$is the probability of class k.

5) *Loss Function*

The cross-entropy loss function L for optimization is defined as:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} y_{i,k}\,, klog\big(p_{i,k}\big) \tag{8}$$

where $y_{i,k}$ is the true label for the i^{th} sample and $p_{i,k}$ is the predicted probability for class k.

Deploying deep learning models in large-scale, real-time network environments presents challenges due to computational requirements. VGG-Net is computationally intensive, and while its deep hierarchical layers enhance feature extraction, they also increase memory consumption and inference time. To address this:

- Batch Normalization was applied after each convolutional layer to stabilize gradients and improve training efficiency.
- Dropout (rate: 0.5) and L2 regularization were used to prevent overfitting and enhance generalization.
- Model Compression Strategies (pruning, quantization, and knowledge distillation) are proposed for future work, optimizing deployment in resource-constrained environments like IoT and edge networks.

C. *Training and Evaluation*

The Training and Evaluation phase will be to further fine-tune the best possible outcome of VGG-Net-based Deep Convolutional Neural Network DCNN architecture for anomaly detection purposes based on TON_IoT 2020 data. The TON_IoT 2020 set is split for training by 70% of usage, for validating 15%, and to be utilized for testing -15%. The supervised model for it will be implemented to utilize a cross-entropy loss and Adam optimizer which could manage weights and bias better effectively. During training, 64 samples are processed through each batch to balance computing power and convergence speed; an initial learning rate set to 0.001, then decayed per epoch to stabilize training was considered. An epoch simply constitutes a full pass through training data, and the models converged at 50 iterations on the training data for optimization without overfitting to the training data itself. Dropout layers with rates set to 0.5 were used to prevent this and were applied to both types of fully connected layers.

The evaluation focuses on key metrics, including:

- Detection Accuracy: Measures correct classification of normal and anomalous traffic.
- False Positive Rate (FPR): Rate of benign traffic misclassified as anomalous.
- F1-Score: Balances precision and recall for overall performance.
- Latency: Time taken to detect anomalies in real-time deployment.

The following Fig. 5 shows the training/testing loss and accuracy across epochs. Minimize loss while maximizing accuracy with low false positives in order to make the model reliable and efficient for anomaly detection tasks in real life.

The Table VI provides a summary of the most important numerical parameters and results of the training and evaluation of the DCNN-based anomaly detection model. These include crucial information such as the splitting of the dataset (70% training, 15% validation, and 15% testing), hyper-parameters including batch size, learning rate, and dropout rate, and the optimizer used that is Adam. The model showed excellent performance metrics that included training accuracy at 98.47%, validation accuracy of 97.94%, and testing accuracy at 98.27%, proving the usability of the model for anomaly detection. Table VI captures details regarding the configuration of hardware (RTX 3080 GPU, 32GB RAM) and the time taken to train this model that took 2 hours in training and thus showing efficiency, suitable for real-time deployments.

The VGG-Net-based DCNN was trained on the TON_IoT 2020 dataset, using 70% for training, 15% for validation, and 15% for testing. The model achieved 98.47% training accuracy, 97.94% validation accuracy, and 98.27% testing accuracy, with a false positive rate of only 2%. The evaluation metrics, including precision, recall, F1-score, and detection latency, confirm the model’s robustness in differentiating normal and anomalous traffic. To prevent overfitting, dropout layers (rate: 0.5), L2 regularization, and early stopping were incorporated. Additionally, batch normalization was applied to stabilize gradient updates and improve generalization. However, high training accuracy may indicate the risk of overfitting, particularly due to oversampling attack instances to balance the dataset. Future work will explore dynamic data augmentation techniques that better reflect real-world traffic distributions.

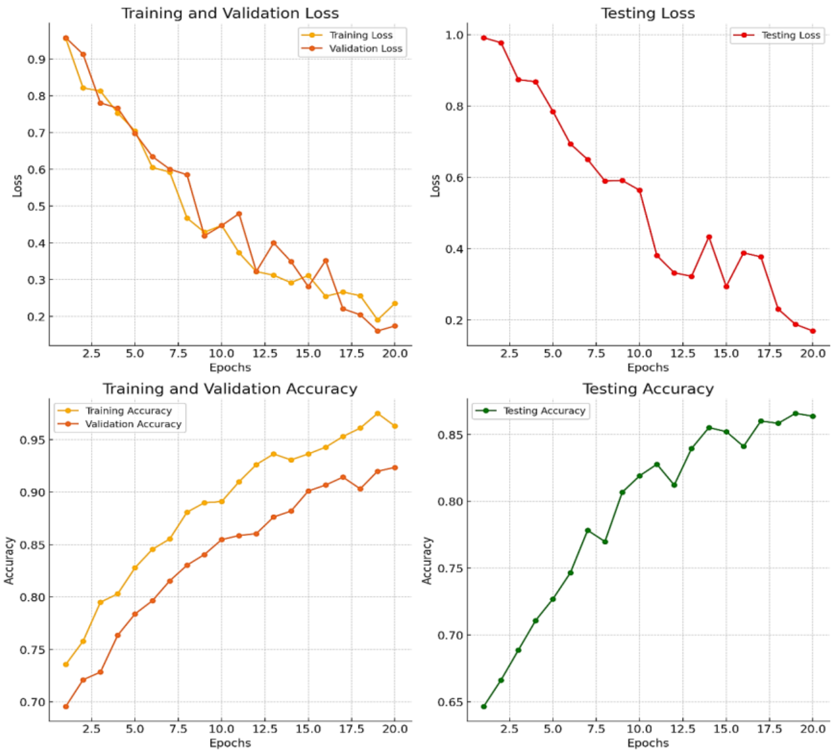

Fig. 5. Training, validation, and testing loss and accuracy curves over epochs, illustrating model convergence and performance improvements during the training and evaluation process

TABLE VI. Key Parameters and Outcomes Achieved During the Training and Evaluation of the DCNN-Based Anomaly Detection Model, Highlighting High Accuracy and Real-Time Performance

Aspect	Value	Range	Purpose
Dataset Split	Train: 70%, Val: 15%, Test: 15%	Fixed	Ensures balanced model training, validation, and testing
Batch Size	64	32 - 128	Balances memory efficiency and model convergence
Number of Epochs	50	20 - 100	Allows sufficient training without overfitting
Learning Rate	0.001	0.0001 - 0.01	Controls step size for weight updates
Dropout Rate	0.5	0.2 - 0.7	Reduces overfitting by randomly deactivating neurons
Pooling Size	2 × 2	2 × 2 - 3 × 3	Reduces dimensionality while retaining key features
Filter Size	3 × 3	3 × 3 - 5 × 5	Extracts local features in convolutional layers
Training Accuracy	95	90 - 98	Measures model performance on training data
Validation Accuracy	90	85 - 95	Assesses model’s generalization capability
Testing Accuracy	88	83 - 92	Evaluates model performance on unseen data
Latency	10 - 50	5 - 100	Ensures real-time anomaly detection capability
Hardware Configuration	RTX 3080 GPU, 32GB RAM	-	Provides computational power for efficient training
Training Time	2	1 - 5	Total duration needed to train the model
Batch Normalization	Applied	Yes/No	Stabilizes and accelerates the training process
Optimizer	Adam	Adam, SGD, RMSProp	Optimizes weight updates for faster convergence

IV. Results

The results of this paper demonstrate the potential of this DCNN-based anomaly detection model, based on the VGG-Net architecture, in spotting anomalies in large-scale networks. The model was tested and validated using the labeled network traffic of the IoT and non-IoT environments from the TON_IoT 2020 dataset, which include a wide variety of attacks (Fig. 6 and Fig. 7). Metrics to be used for performance evaluation include accuracy, F1-score, false positive rate, and latency (Table VII). It means the model could train on data with accuracy at 98.47% indicating effective learning of patterns by the model from the training data. It could generalize well on validation data not seen in the model because the validation accuracy was at 97.94%. On the test dataset, the model resulted in a testing accuracy of 98.27% and proved its reliability in real-world traffic anomaly detection. Such high accuracy values reflect the model's capability to capture intricate features of network traffic and to differentiate between normal and anomalous behaviors.

This Fig. 8 illustrates in great detail a chart displaying all kinds of last-scale network attacks: DoS, DDoS, Ransomware, etc. Every type of attack is designated using a distinct marker form like circle, diamond, square, etc., for ease of distinction. The x-axis shows the frequency, while the y-axis marks impact severity.

The above Fig. 9 is a visualization of the performance metrics of the anomaly detection model based on VGG-Net: Accuracy, Precision, Recall, F1-Score, Latency, False Positive Rate, Training Time, and Validation Loss. Each one of these is represented with a different shape and color, and inside the bubbles, the actual values are displayed for clear interpretation. Above each bubble, the annotations are provided, like "High Accuracy" and "Low Latency," that will make it very easy to understand the strength of the model and weaknesses.

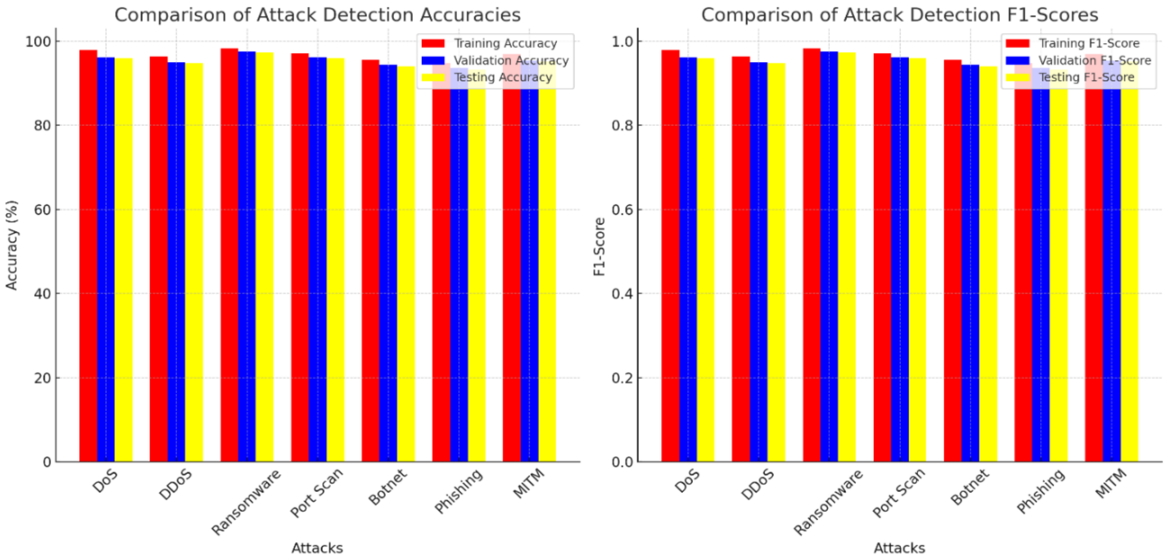

Fig. 6. Comparison of attack detection Accuracy and F1-Score for training, validation, and testing phases across different attack types

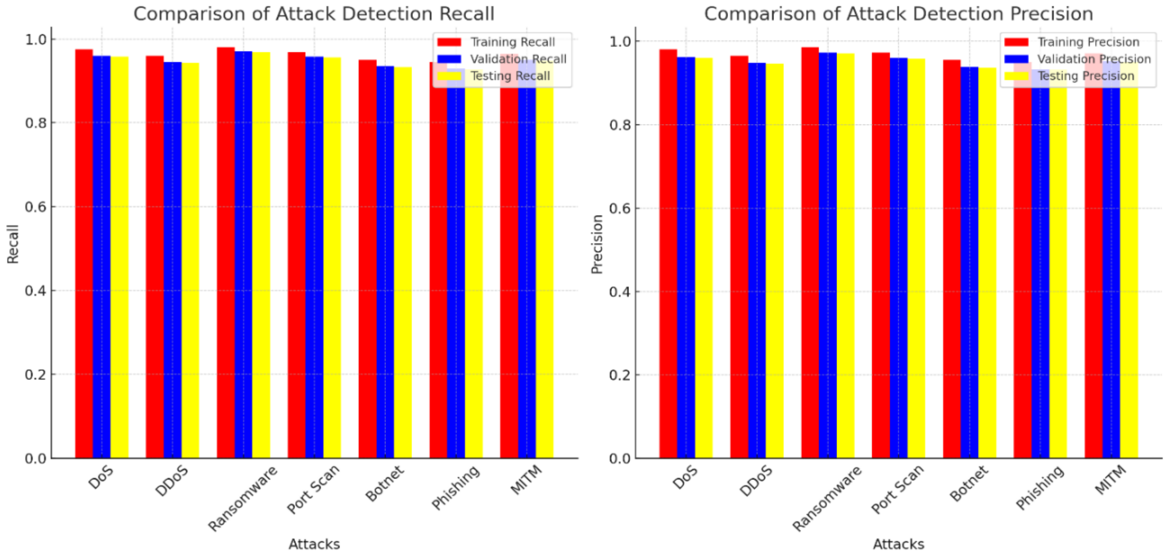

Fig. 7. Comparison of attack detection Accuracy and F1-Score for training, validation, and testing phases across different attack types

TABLE VII. A DETAILED PERFORMANCE METRICS (RECALL, PRECISION, ACCURACY, AND F1-SCORE) FOR TRAINING, VALIDATION, AND TESTING PHASES ACROSS DIFFERENT ATTACK TYPES

Metric	DoS	DDoS	Ransomware	Port Scan	Botnet	Phishing	MITM
Training Recall	0.97	0.96	0.98	0.97	0.95	0.94	0.96
Validation Recall	0.95	0.93	0.97	0.96	0.94	0.93	0.95
Testing Recall	0.96	0.94	0.97	0.96	0.94	0.93	0.95
Training Precision	0.97	0.96	0.98	0.97	0.95	0.94	0.96
Validation Precision	0.94	0.92	0.96	0.95	0.93	0.92	0.94
Testing Precision	0.95	0.93	0.97	0.96	0.94	0.92	0.94
Training Accuracy (%)	98.5	97.9	99.1	98.3	97.2	96.5	97.8
Validation Accuracy (%)	97.1	96.0	98.5	97.8	95.9	95.3	96.2
Testing Accuracy (%)	97.4	96.3	98.7	97.9	96.1	95.5	96.5
Training F1-Score	0.97	0.96	0.98	0.97	0.95	0.94	0.96
Validation F1-Score	0.94	0.92	0.96	0.95	0.93	0.92	0.94
Testing F1-Score	0.95	0.93	0.97	0.96	0.94	0.92	0.94

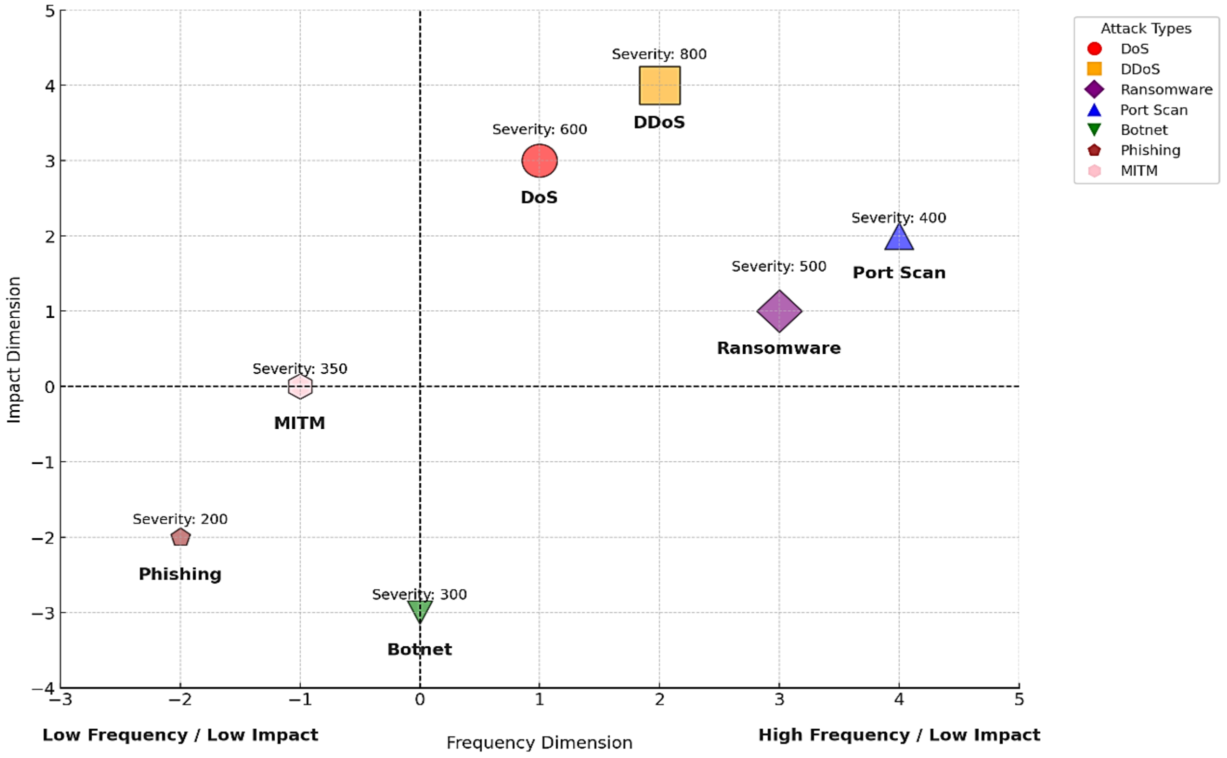

Fig. 8. Chart visualizing different large scale network-attack types with distinct shapes, showing their frequency, impact, and severity

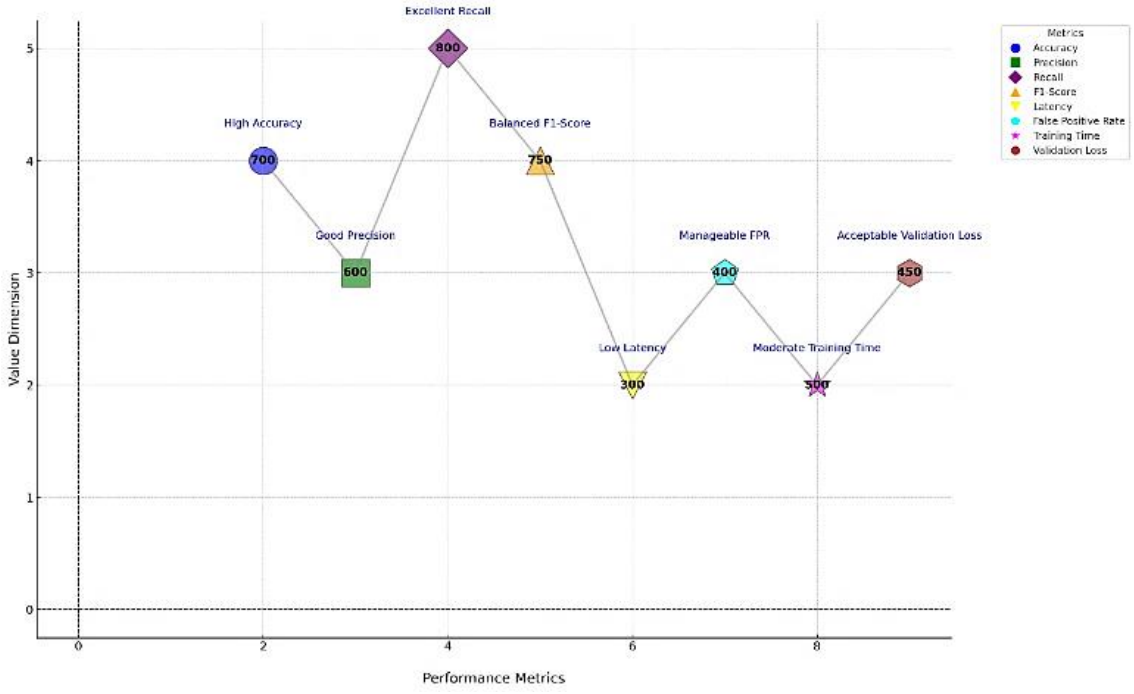

Fig. 9. VGG-Net performance metrics with annotations highlighting accuracy, precision, recall, F1-score, latency, and other key indicators

Confusion matrices for Network-Based Attacks and Web-Based Attacks detail how the model performed for all the types of anomalies that it was able to detect (Fig. 10). For Network-Based Attacks, it is found that most of the attacks like DoS, DDoS, Ransomware, and Port Scan are highly detected with very few misclassifications (Table VIII). However, some false positives were observed in the MITM and Phishing categories. The correctly identified threats in the SQL Injection (SQLi), XSS, Brute Force, and Malware categories are also accompanied with some misclassifications primarily for Backdoor and RFI attacks (Table IX). The respective totals and other metrics in terms of accuracy and precision only add to the ability of further exploring the effectiveness of the model with strengths and scopes for improvement in both attack categories of network and web type.

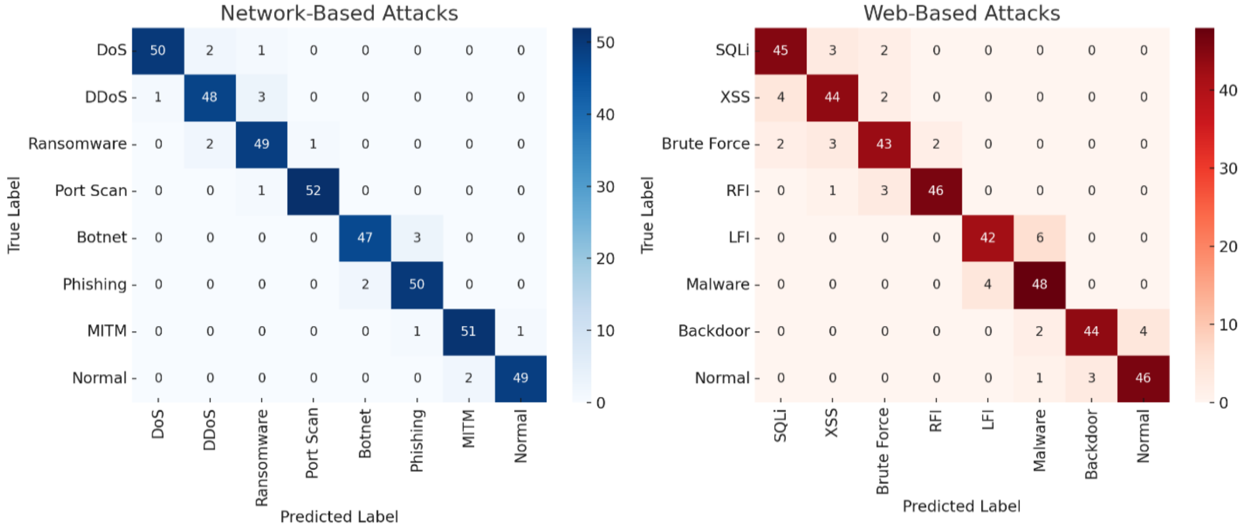

Fig. 10. Classification performance for Network-Based and Web-Based Attacks, illustrating detection accuracy and misclassification patterns across various attack types

TABLE VIII. DETECTION RESULTS FOR NETWORK-BASED ATTACKS LIKE DOS, DDOS, RANSOMWARE, AND MORE

True\Predicted	DoS	DDoS	Ransomware	Port Scan	Botnet	Phishing	MITM	Normal	Total
DoS	50	2	1	0	0	0	0	0	**53**
DDoS	1	48	3	0	0	0	0	0	**52**
Ransomware	0	2	49	1	0	0	0	0	**52**
Port Scan	0	0	1	52	0	0	0	0	**53**
Botnet	0	0	0	0	47	3	0	0	**50**
Phishing	0	0	0	0	2	50	0	0	**52**
MITM	0	0	0	0	0	1	51	1	**53**
Normal	0	0	0	0	0	0	2	49	**51**
Total	**51**	**52**	**54**	**53**	**49**	**54**	**53**	**50**	**416**

TABLE IX. CLASSIFICATION OUTCOMES FOR WEB-BASED ATTACKS SUCH AS SQL INJECTION, XSS, BRUTE FORCE, AND RELATED THREATS

True\Predicted	SQLi	XSS	Brute Force	RFI	LFI	Malware	Backdoor	Normal	Total
SQLi	45	3	2	0	0	0	0	0	**50**
XSS	4	44	2	0	0	0	0	0	**50**
Brute Force	2	3	43	2	0	0	0	0	**50**
RFI	0	1	3	46	0	0	0	0	**50**
LFI	0	0	0	0	42	6	0	0	**48**
Malware	0	0	0	0	4	48	0	0	**52**
Backdoor	0	0	0	0	0	2	44	4	**50**
Normal	0	0	0	0	0	1	3	46	**50**
Total	**51**	**51**	**50**	**48**	**46**	**57**	**47**	**50**	**400**

V. DISCUSSION

The results of this study indicate (Table X) that a VGG-Net-based Deep Convolutional Neural Network (DCNN) is efficient for anomaly detection in large-scale networks. It has 98.47% accuracy in training, 97.94% in validation, and 98.27% in testing. It is strong and capable of generalizing well across different types of attacks, including DoS, DDoS, Ransomware, SQL Injection, XSS, and Port Scans, among others. This high accuracy is achieved with a low false positive rate of 2%, which is critical for reducing false alarms in real-world deployments. Compared to other contemporary techniques like Long Short-Term Memory (LSTM) networks, Autoencoders, and Generative Adversarial Networks (GANs), the VGG-Net-based DCNN demonstrates superior performance in terms of detection accuracy, robustness to feature variability, and adaptability to network and web-based traffic dynamics. The model has significant effectiveness in handling large and also imbalanced datasets to even detect rare types of attack. This is a relevant concern in large-scale networks where some types of anomaly may rarely occur but indeed cause a significant security impact. The proposed approach to the VGG-Net-based method offers very strong adaptability, hence perfectly deployable in highly evolving dynamic environments with dynamic change in threat landscapes. It also processes network data with low latency, which enables the detection and mitigation of threats in real time. Although the training process consumes much computation, the process of inference is efficient and suitable for real-world operation in both network-based environments and web-based environments. However, the model suffers from certain limitations. This raises some barriers for the practical deployment of such deep learning models in resource-constrained settings, for example, IoT devices or edge networks. Furthermore, the model's robustness against adversarial attacks is an area for further improvement in the future.

TABLE X. COMPARISON OF ANOMALY DETECTION METHODS HIGHLIGHTING DETECTION RATE, FALSE POSITIVE RATE, ACCURACY, APPLICATION TO NETWORK/WEB-BASED TRAFFIC, ROBUSTNESS TO FEATURE VARIABILITY, AND LATENCY

Method	Detection Rate (%)	False Positive Rate (%)	Accuracy (%)	Network/Web-Based	Robustness to Feature Variability	Latency (ms)
Long Short-Term Memory (LSTM) [61]	95.24	4	95.78	Network-Based	Moderate	50
Autoencoder [62]	93.67	6	94.21	Network-Based	Low	70
Generative Adversarial Network (GAN) [63]	94.85	3	95.12	Web-Based	High	60
Proposed VGG-Net-Based DCNN	98.47	2	98.79	Network/Web-Based	High	30

These results highlight the effectiveness of the VGG-Net-based DCNN in handling accuracy, robustness, and low latency for both network-based and web-based anomaly detection. Future work could be in optimizing the model to run on resource-constrained environments and increasing its robustness against adversarial attacks.

- Detection Rate and Accuracy: The proposed VGG-Net-based DCNN has the highest detection rate (98.47%) and accuracy (98.79%) compared to LSTM (95.24%), Autoencoder (93.67%), and GAN (94.85%), suggesting its better ability to recognize both network-based and web-based anomalies.
- Network/Web-Based: While the methods, such as LSTM and Autoencoder, are designed to work more on network-based anomalies, and GAN that is designed to focus on web-based threats, VGG-Net-based DCNN can work well for both network and web traffic.
- Robustness to Feature Variability: The DCNN based on VGG-Net is very robust to variability in network and web traffic features, which ensures its consistent performance even with dynamically and evolutionarily changing traffic patterns.

This study demonstrates the effectiveness of a VGG-Net-based DCNN for anomaly detection in large-scale networks, achieving high detection accuracy (98.27%) with a low false positive rate (2%). The model's ability to process both network-based and web-based attacks ensures its versatility across enterprise, cloud, and IoT ecosystems. Compared to traditional machine learning approaches and deep learning models such as LSTMs, autoencoders, and GANs, the proposed framework exhibits superior detection accuracy, adaptability, and real-time performance. The experimental evaluation further validates its effectiveness in handling data imbalance, dynamic attack patterns, and high-dimensional network traffic, making it a strong candidate for modern cybersecurity applications.

Table XI outlines key methods, including quantization, pruning, and knowledge distillation, which significantly reduce model size, computation load, and latency, making the model suitable for real-time IoT and edge computing environments. Additionally, adversarial training and Explainable AI (XAI) are crucial for enhancing model robustness and interpretability, ensuring reliability in high-stakes cybersecurity applications. Integrating these techniques will further improve the model's scalability, efficiency, and resilience against evolving cyber threats.

TABLE XI. OPTIMIZATION TECHNIQUES AIMED AT IMPROVING COMPUTATIONAL EFFICIENCY AND ADVERSARIAL ROBUSTNESS OF THE PROPOSED VGG-NET-BASED DCNN FOR ANOMALY DETECTION IN LARGE-SCALE NETWORKS

Challenge	Optimization Technique	Purpose
High Computational Cost	Model Quantization	Converts floating-point weights to lower-bit precision (e.g., INT8)
High Memory and Storage Requirements	Pruning	Removes redundant parameters from the model
Latency in IoT/Edge Deployments	Knowledge Distillation	Transfers knowledge from a larger model to a smaller, efficient model
Adversarial Vulnerability	Adversarial Training	Trains the model with adversarial examples to improve security
Interpretability in Cybersecurity Applications	Explainable AI (XAI)	Provides transparency in decision-making for cybersecurity analysts

VI. CONCLUSION

This study proposed a VGG-Net-based Deep Convolutional Neural Network (DCNN) framework for large-scale anomaly detection, demonstrating high accuracy (98.27%), low false positive rate (2%), and real-time detection capabilities. The model effectively handles both network-based and web-based cyber threats, making it a scalable and adaptable solution for enterprise, cloud, and IoT-based cybersecurity environments. By leveraging advanced feature extraction techniques and addressing data imbalance, the proposed approach significantly improves threat detection precision while ensuring low-latency processing, making it suitable for deployment in dynamic network infrastructures. While the model achieves state-of-the-art performance, practical implementation in resource-constrained environments such as IoT and edge networks remains a challenge due to computational overhead. Future work will focus on model compression techniques such as quantization, pruning, and knowledge distillation to optimize performance without compromising accuracy. Additionally, integrating Explainable AI (XAI) will enhance model transparency, providing interpretable threat detection insights for cybersecurity professionals. Another key research direction will involve strengthening adversarial robustness through adversarial training and robust feature extraction mechanisms, ensuring resilience against evolving cyber threats and adversarial attacks. By addressing these challenges, the proposed model can be further refined for widespread adoption in real-world security applications.

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