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CYBERSECURITY AND DATA QUALITY MANAGEMENT IN AI-DRIVEN SUSTAINABLE HEALTHCARE SYSTEMS

Mohan Harish Maturi[1], Karthik Meduri[1], Geeta Sandeep Nadella[1*], Snehal Satish[1], Hari Gonaygunta[1]
[1]Department of Information Technology, University of the Cumberlands, Williamsburg, 40769, KY, USA

*Corresponding Author: gnadella3853@ucumberlands.edu

ABSTRACT

The increasing prevalence of cybersecurity threats and the critical need for high-quality data in healthcare systems pose significant challenges to data integrity, secrecy, and safety. Very complex Healthcare info is vulnerable to breaches and anomalies, which is essential to implement robust ways to categorize potential threats and measure data quality. This study investigates the use of machine-learning models to calculate cybersecurity tasks and assess the data quality in healthcare using the 2019 secondary dataset. The variation of procedures with XGBoost, LightGBM Random-Forest Logistic-Regression, Decision-Trees, and models were evaluated for their skill in identifying anomalies and measuring data integrity. The results indicate that ensemble models with XGBoost (99.98% accuracy) outperform simpler models like logistic Regression and decision trees, which showed higher misclassification rates. The superior presentation of collective methods highlights the complexity of cybersecurity threats and the accuracy of healthcare data. These findings emphasize the significance of using progressive machine-learning procedures in critical sectors like healthcare, where data quality and security are paramount.

KEYWORDS: Cybersecurity, Data Quality, AI, Healthcare Systems, Sustainability, Systematic Review

1. INTRODUCTION

Artificial Intelligence (AI) transforms modern healthcare systems by enhancing diagnosis, treatment, and overall patient care. AI-powered tools and algorithms are faster and more accurate identification of diseases, personalized treatments, and more efficient hospital operations [1]. The progressions in machine-learning, deep-learning, and natural-language processing and healthcare professionals AI to interpret complex health statistics, including imaging scans, genomic data, and patient records [2]. These competencies not only improve clinical outcomes but also help reduce human error in critical healthcare decisions [3]. Sustainability in healthcare is a key focus as the global populations rise and healthcare costs increase. AI offers the potential to optimize resource utilization, streamline workflows, and reduce waste. AI can assist in the predictive maintenance of medical equipment, reducing downtime and unnecessary costs [4]. AI can help prevent hospital readmissions by predicting patient outcomes and guiding early intervention. The AI in telemedicine and remote monitoring also promotes sustainability by reducing the need for physical visits and cutting down on the carbon footprint associated with travel [5][6]. AI's contribution to a more efficient, accessible, and sustainable healthcare system is evident, as well as better allocation of resources while maintaining high standards of care.

AI is embedded in healthcare systems, and the importance of Cybersecurity is growing exponentially. AI-driven healthcare systems handle huge quantities of sensitive patient data, counting Electronic-Health-Records (EHRs) analytic and genomic information. This file is highly valuable for improving patient care and is a prime target for cyberattacks [7]. Breaches of healthcare statistics and simple significances with financial losses, cooperated patient privacy, and even risks to patient safety. Cybersecurity is serious in reliability, privacy, and obtainability of AI schemes in healthcare. AI models handle personal health data and need protection from external threats such as ransomware, phishing, and malware attacks [8]. Adversarial attacks are where malicious actors manipulate AI models by introducing false data, incorrect diagnoses or treatment plans, and endangering patients' lives. The robust cybersecurity measures are encryption, regular software updates, and multi-factor authentication, which is vital to prevent unauthorized access and maintain trust in AI-driven healthcare systems [9]. Healthcare providers are implementing stringent data governance and compliance frameworks to follow rules like HIPAA (Health-Insurance-Portability and Accountability Act) and GDPR (General-Data-Protection-Regulation), safeguarding patient information and the AI systems that rely on it.

Data is the lifeblood of AI systems in healthcare, and the excellence of data directly influences the performance and reliability of AI models [10]. High-quality, accurate, well-structured data and AI systems provide meaningful and accurate predictions and support healthcare professionals ' learned choices. Conversely, poor quality data and unreliable AI performance, including inaccurate diagnoses, flawed treatment recommendations, and biased outcomes, can harm patients and undermine trust in AI. In healthcare, data comes from varied bases: medical records, laboratory results, imaging systems, and wearable devices [11]. Managing this data involves accuracy, standardizing formats, and addressing missing values, inconsistencies, and noise. Data cleaning, integration, and validation are critical to maintaining high-quality datasets [12]. These predictive analytics and the copy's correctness rest on the relevance and precision of the preparation statistics. AI scheme experts on partial or imperfect data may continue the healthcare access or outcomes gaps. Maintaining data quality is paramount to achieving fairness and reliability in AI applications.

1.1 Research Focus

The research explores the integration of artificial intelligence (AI) and machine-learning models to improve Cybersecurity and data quality management in AI-driven healthcare systems. The growing support of AI technologies in healthcare, protecting subtle medical files, and maintaining high data quality is critical to system reliability and patient safety [10]. This reading aims to analyze machine-learning approaches in sensing and mitigating cybersecurity threats while addressing data quality tasks to donate to the growth of maintainable and secure healthcare organizations.

1.2 Significance of study

Here A few key steps of objective and study significance are listed below:

1. Investigate the character of machine-learning models in improving Cybersecurity in AI-driven healthcare systems and detecting and mitigating potential threats.
2. Analyze the impact of data quality on the reliability and performance of AI models in healthcare settings.
3. Using secondary datasets, calculate different machine-learning copies in managing Cybersecurity and data quality issues.
4. Provide recommendations for enhancing healthcare systems' sustainability with improved AI-driven cybersecurity measures and data management practices.

2. LITERATURE REVIEW

In healthcare with applications ranging from diagnostics to patient monitoring and administrative efficiencies. AI-driven healthcare systems use advanced machine-learning algorithms, deep-learning models, and natural-language processing to examine large volumes of medical facts and help clinicians make more accurate and timely decisions [13]. Key applications include AI-assisted diagnostic tools that analyze imaging data (e.g., X-rays, CT scans, MRIs) to accurately detect cancer conditions, cardiovascular diseases, and neurological disorders. AI-powered platforms are personalized medicine that predicts the cure tactics created based on the patient's genetic makeup and medical history. In sustainability, AI is essential in adjusting healthcare maneuvers, reducing costs, and efficiently using resources. AI predicts hospital readmissions or helps allocate medical staff and equipment more, minimizing waste and improving patient outcomes [14]. The use of AI in telemedicine and distant patient checking also contributes to sustainability in falling the necessity for in-person appointments and Hospitalizations, which lowers energy consumption, resource use, and carbon emissions associated with healthcare facilities. AI supports public health initiatives by forecasting the extent of infectious diseases, assisting in early intervention efforts, and helping health systems manage outbreaks [15].

These healthcare systems globally face growing demand due to aging populations, chronic disease prevalence, and economic constraints. AI's capacity to promote sustainable healthcare delivery is becoming increasingly vital [16]. It provides scalable solutions that enhance access to care, reduce the burden on healthcare providers, and optimize resource utilization, all while maintaining or improving care quality. Addressing the sustainability challenge and AI contributes to the long-term viability of healthcare systems and allows these systems to continue to pay great attention to all populations in resource-constrained settings [17].

Cybersecurity is a serious alarm in AI-driven healthcare systems as these organizations manage huge quantities of subtle patient information, counting medical records, genetic information, and treatment histories [18]. Integrating AI into healthcare introduces unique cybersecurity challenges because AI models rely on large datasets and advanced algorithms, as well as compromised and serious patient confidentiality and data integrity breaches. Previous studies have highlighted that healthcare is one of the most targeted industries for cyberattacks, with breaches resulting in financial losses, personality theft, and disruptions to critical healthcare services. One prominent example is the risk of ransomware attacks, where hackers encode healthcare data and request expenses to repair admittance, severely disrupting patient care [19][20].

AI in healthcare also introduces specific risks related to adversarial attacks where malicious actors manipulate the inputs of AI models to produce incorrect outputs, misdiagnoses, or inappropriate treatment recommendations [21-22]. This is dangerous in clinical decision-making systems that rely on AI to assist healthcare professionals in diagnosing and treating patients. If these systems are fed tampered data, the consequences can be life-threatening. AI models inadvertently amplify privacy concerns because they require huge amounts of information. In training models, sensitive patient data is shared in various platforms and systems, increasing the risk of unauthorized access or misuse. Studies on healthcare data breaches emphasize that existing cybersecurity frameworks in healthcare may not be sufficient to address the new risks posed by AI-driven systems [23]. Many healthcare providers lack the infrastructure and expertise to safeguard AI systems against sophisticated cyber threats. The healthcare systems must comply with stringent controlling frameworks like HIPAA and GDPR, which impose strict data protection and privacy rules. Compliance with maintaining the efficiency of AI models presents another layer of complexity for healthcare organizations [24].

Healthcare files are produced from varied bases, such as Electronic-Health-Records (EHRs) and Medical-Imaging-Systems, which are laboratory tests, wear-able instruments, and patient-generated data [25-26]. This data must be accurate and free from discrepancies for the AI systems to function. The missing values in patient records cause AI models to misinterpret a patient's condition and potentially harmful recommendations. The duplicate or outdated data distort AI predictions and misguide healthcare professionals. Healthcare data quality involves rigorous data cleaning, normalization, and validation processes to eliminate inconsistencies, fill gaps, and standardize the data format [27].

The reliability of healthcare facts is supreme for the fairness and safety of AI applications. Poor data quality introduces biases in AI models and unequal treatment of different patient groups. If certain populations are underrepresented in the training data, AI systems may fail to accurately predict those groups and perpetuate healthcare disparities [28]. Maintaining high data quality is essential for AI performance and ethical and equitable healthcare outcomes.

Machine learning (ML) is progressively important in enhancing cybersecurity and information management in healthcare schemes [29]. With healthcare facts being the major aim for cyber-attacks due to their sensitive nature, ML models are used to notice and alleviate cybersecurity fears by examining network traffic designs, user behavior, and system activities. The main advantages of ML in healthcare security are its capacity to absorb huge quantities of info, adapt to new threats, and identify previously unknown vulnerabilities in real time. ML is essential in the ongoing battle against cyber threats, such as ransomware attacks, data breaches, and phishing scams [30].

3. METHODOLOGY

This chapter outlines the methodology for analyzing distributed denial-of-service (DDoS) assaults with machine-learning models. The analysis begins with selecting the DDoS Evaluation Dataset developed by the Canadian Institute for Cybersecurity, which provides a realistic representation of equally benign plus malicious traffic essentials for effective anomaly detection [31]. The chapter details the preprocessing steps required to prepare the data, including data cleaning, normalization, and the division into training and testing sets. It also highlights the importance of feature engineering, which is when relevant attributes are selected from the Dataset to enhance ML model performance. The AI model implementations to evaluate their performance in different metrics and visualizations [32]. The contracted framework of this analysis is given below in Figure 1.

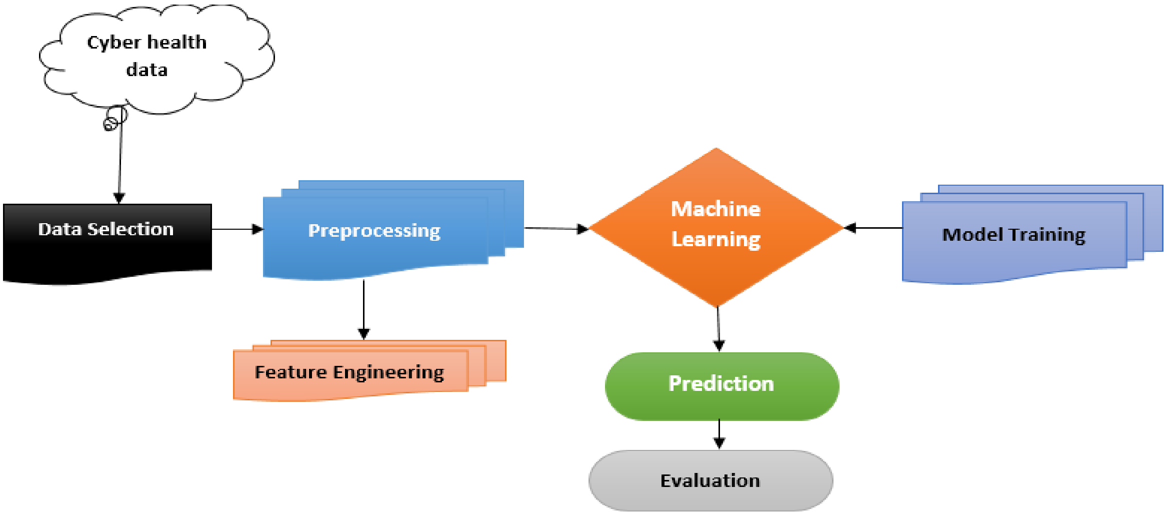

Figure 1: Proposed Framework

3.1 Data Selection

The DDoS Evaluation Dataset (CIC-DDoS2019), advanced in the Canadian-Institute-Cybersecurity, is designed to deliver realistic and comprehensive data for finding Distributed-Denial-of-Service (DDoS) assaults [33]. These datasets comprising benign and malicious traffic collected from multiple devices are highly suitable for machine-learning-based anomaly detection. It contains over 200,000 columns representing the various features extracted from packet captures (pcap) using the CICFlowMeter-V3 tool, differentiating between DDoS attacks and normal traffic. The information's variety and size are ideal for preparing advanced machine-learning copies to analyze altered DDoS attack types robustly. Due to its large size and the presence of DDoS patterns mixed with benign traffic, this Dataset offers a challenging platform for cybersecurity research and testing of anomaly detection algorithms [34].

3.2 Data preprocess

Preprocessing is vital to the machine-learning copies skilled on the secondary Dataset that can identify DDoS attacks [35].

- The Dataset includes some challenges: inconsistent column names (e.g., spaces before headers) and potential missing values that must be addressed.
- The data cleaning involves renaming columns to uniformity, removing irrelevant or redundant features, and handling missing or erroneous data entries.
- Lost data can be handled through imputation (mean, median, and mode) or removing rows or columns if the missing values are significant.
- Normalization of the data is also crucial since some features like packet sizes or flow durations may have large variations in scale. Min Max climbing or z score standardization can bring all features within the same range, and no single feature disproportionately influences the copy's recital.

The last step includes sharing the datasets to prepare and test collections and maintaining the balance between benign and DDoS attack data for unbiased model evaluation.

3.3 Feature Engineering

Feature engineering plays a serious part in refining the presentation of machine-learning copies for cybersecurity tasks. In the context of the CIC-DDoS2019 dataset, selecting relevant features from the huge set of over 200,000 columns is necessary to focus the analysis on the most impactful attributes [34]. Key features may include packet size, flow duration, source and destination IP addresses, number of packets sent inter-arrival times, and flags (SYN, ACK, and FIN) commonly associated with DDoS attacks. These features help identify abnormal traffic patterns, such as high packet rates or irregular flow times, which are indicators of DDoS attacks. Dimensionality decreases procedures like Principal-Component-Analysis (PCA), which can also reduce the feature space while retaining the most informative attributes and improving model efficiency without sacrificing accuracy [36].

3.4 Machine Learning Models

This analysis implemented the different ML models to predict cyber threats and measure the data quality in health systems; the models are listed below:

- **Logistic Regression**: the arithmetical method used for two organization chores is ideal for identifying whether a system is under attack. It copies the prospect of two results fitting data to the logistic curve and transforming it to output values among the 0 and 1. Cybersecurity and logistic Regression can be employed to classify network traffic or system activities as benign or malicious, and they work well when the association between the structures and the goal is nearly linear [37].
- **XGBoost (Extreme Gradient Boosting)** is the robust collective knowledge method that forms the decision trees successively, where each new tree modifies the faults of the earlier ones. It uses gradient boosting but optimizes speed and performance for real-time cybersecurity applications like intrusion detection systems (IDS). XGBoost excels at detecting complex patterns within large datasets and is useful in identifying subtle cybersecurity threats and boosting the accuracy of predictions with each iteration [38].
- **LightGBM (Light Gradient Boosting Machine)**: This algorithm remains the fastest, most efficient, and most highly scalable gradient boosting algorithm and is designed to handle large-scale datasets. It uses the histogram-based algorithm for data binning and splits tree leaves, which speeds up the model training process. LightGBM is suitable for cybersecurity tasks where low latency and scalability are critical, such as detecting distributed denial-of-service (DDoS) attacks or anomalies in large network traffic logs [39].
- **AdaBoost (Adaptive Boosting)**: The other collective knowledge combines frail beginners (typically decision trees) to generate the robust classifier: each following learner and the errors made in the earlier ones. In Cybersecurity, AdaBoost can help detect low-frequency cyberattacks that other models miss. Its adaptive nature to fine-tune the detection of more elusive and sophisticated cyber threats [40].
- **Random Forest**: Random ensemble of decision trees where each tree is skilled on the random subset of the data. The last calculation is made in the fallouts of all the trees. Random forests are known for their toughness and

capacity to grip overfitting for detecting a wide range of cyberattacks, such as phishing, malware detection, and system intrusions. They work well with high-dimensional datasets found in Cybersecurity [41].

- **Gradient Boosting**: Gradient is the sequential ensemble technique that builds models iteratively to minimize the earlier copies' prediction errors. Each new model in the arrangement is trained to correct the errors of the previous ones. Cybersecurity and Gradient Boosting are used to identify complex attack patterns and anomalies and continuously refine their predictions to detect known and unknown threats [42].

3.5 Model Evaluation

In the machine-learning workflow in the cybersecurity background, the accuracy of predictions significantly impacts system security. This process involves assessing each model's performance using many metrics: exactness, correctness and recall, F1-score, and area under the Receiver-Operating-Characteristic (ROC) curve (AUC-ROC). Exactitude deals with the proportion of correct estimates, while correctness and recall are delivered into the model's capacity to identify true positive attacks versus false positives. The F1 score balances precision and recall and is valuable in scenarios with class imbalances distinguishing between benign and malicious traffic [43]. AUC-ROC calculates the copy's capacity to distinguish among the classes in many beginning levels. Cross-validation methods are also active in the robustness of the results, helping to moderate over-fitting and providing a more reliable calculation of copies presentation [44]. The evaluation results control the collection of the best-acting models for deployment in real-world cybersecurity applications.

4. RESULTS ANALYSIS

This chapter analyzes the results of the machine-learning models applied to the CIC-DDoS2019 dataset. The performance of each copy is estimated based on key metrics, exactness, and other metrics. The results are analyzed to identify which models were used to detect distributed denial-of-service (DDoS) attacks, and the impact of feature selection and preprocessing steps on model performance is discussed. The comparisons among the models are made to determine the best approach for real-time DDoS detection in cybersecurity applications below Table 1.

Table 1: Numbers of features Outliers

Column	Number of Outliers
Flow ID	0
Source IP	3016
Source Port	0
Destination IP	7223
Destination Port	0
Protocol	0
Timestamp	5089
Flow Duration	3358
Total Fwd Packets	745
Total Backward Packets	652
Total Length of Fwd Packets	14839
Total Length of Bwd Packets	508
Flow Bytes/s	0
Idle Mean	9757
Idle Std	12812
Idle Max	2908
Idle Min	13013
Label	0

The Idle Mean, Idle Std, and Idle Min also have many outliers and suggest irregularities in idle times. These outliers indicate potential anomalies or unusual network behaviors that warrant further investigation.

Table 2: Total outliers detected in Dataset

Step	Description	Number of total outliers
1	Initial Dataset	225,745
2	After Outlier Deduction	133,284

Table 2 shows the impact of outlier removal on the Dataset. The Dataset contained 225,745 rows. After applying the outlier detection process, which involved removing data points that fell beyond three standard deviations from the mean for each of the 37 selected columns, the number of rows was reduced to 133,284. This indicates that a significant portion of the data (approximately 40.9%) was identified as outliers and removed, likely enhancing the Dataset's quality for further analysis and eliminating extreme values.

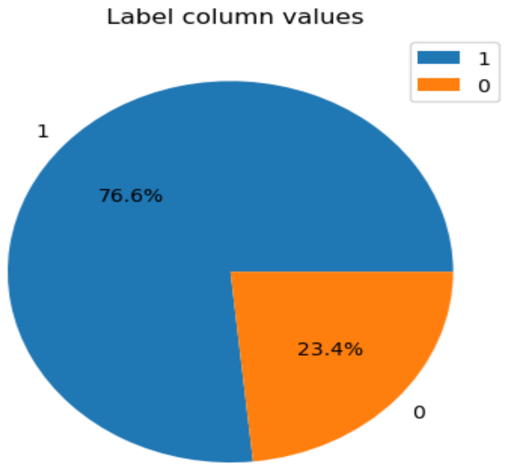

Figure 2:Traffic Benign or Malicious

The Figure 2 pie chart in the first image represents the distribution of the Label column, which likely indicates whether network traffic flow is benign or malicious. The analysis shows that 76.6% of the instances are labeled 1, representing benign traffic, while 23.4% are labeled 0, indicating potentially malicious traffic. This imbalance suggests that the Dataset contains significantly more normal traffic than malicious traffic, a common scenario in cybersecurity datasets. The class imbalance may affect the presentation of machine-learning copies, potentially requiring methods such as resampling or class weighting during model training and detecting malicious activities that are not compromised.

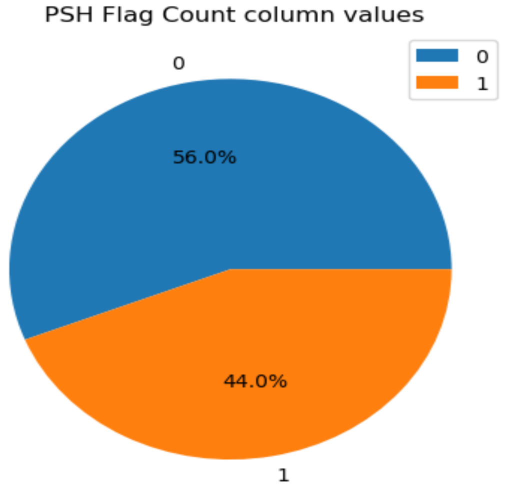

Figure 3: PSH Flag count column

The Figure 3 pie chart displays the distribution of values for the PSH Flag Count column, which counts the number of times the PSH (Push) flag is set in TCP connections. The analysis shows that 56% of the network traffic has no PSH flag set (0), while 44% has the PSH flag set (1). The PSH flag is used in TCP to indicate that data should be pushed to the receiving application without waiting for additional data. A high occurrence of PSH flags could indicate abnormal behavior or malware trying to communicate quickly or establish persistence. Monitoring and analyzing these flags help detect unusual or suspicious patterns in the traffic.

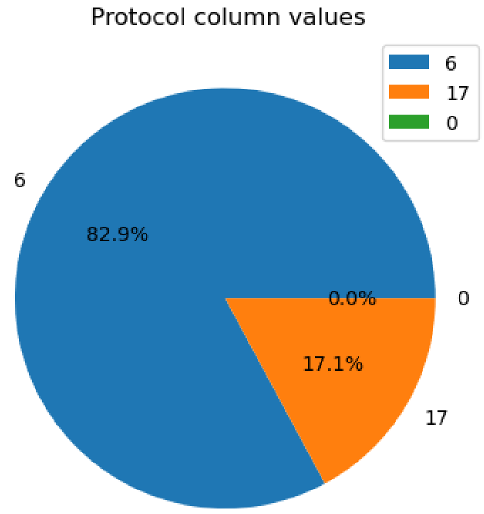

Figure 4: Traffic Protocols

The Figure 4 pie chart illustrates the values of the Protocol column, which shows the different network protocols used in the Dataset. The majority of the traffic (82.9%) is represented in protocol 6 (which usually stands for TCP), while 17.1% of the traffic uses protocol 17 (typically representing UDP). There is a negligible percentage for protocol 0. The dominance of TCP traffic in the Dataset reflects network environments where TCP is the primary protocol for reliable data transmission. The presence of UDP, known for its speed but lack of reliability, may point to specific services or threats, and UDP for quick data transfer potentially poses security risks in Denial of Service (DoS) or amplification attacks.

Table 3: Models Performance Comparison

Models Name	**Accuracy-Score**	**Confusion Matrix**
Logistic Regression	0.94987	[[48784, 2129], [2990, 48215]]
XGBoost (Xgb)	0.99981	[[50909, 4], [15, 51190]]
LightGBM (LGB)	0.99976	[[50904, 9], [15, 51190]]
Decision Tree (Dtree)	0.94042	[[45493, 5420], [664, 50541]]
Random Forest	0.99980	[[50908, 5], [15, 51190]]
AdaBoost (Adb)	0.99966	[[50901, 12], [23, 51182]]
Gradient Boosting	0.99961	[[50899, 14], [26, 51179]]
Bagging	0.99965	[[50902, 11], [25, 51180]]

The above Table 3 results from the machine-learning models, including XGBoost, LightGBM Random-Forest, AdaBoost, and others, demonstrate exceptional accuracy in predicting cybersecurity challenges and assessing data quality in healthcare data. XGBoost achieved the highest accuracy (99.98%), followed closely by LightGBM and Random-Forest with minimal misclassifications. These results indicate that the models are highly identifying anomalies or threats and evaluating the integrity of healthcare data. Logistic regression and Decision-Tree models showed lower performance with a notable number of misclassifications, reflecting the need for more complex algorithms like ensemble methods to handle the intricacies of cybersecurity challenges and healthcare data quality. The high accuracy of ensemble models is XGBoost and Random-Forest and underscores their reliability in tackling sensitive domains like Cybersecurity and healthcare, where precise prediction and quality measurement are critical.

5. CONCLUSION AND DISCUSSION

5.1 Summary of Key Findings

This research proves the significant advancements in Cybersecurity and data quality management within AI-driven healthcare schemes. The combination of machine-learning models are XGBoost, LightGBM, and Random-Forest, and they have been proven to detect cybersecurity threats like distributed denial-of-service (DDoS) attacks. These models displayed high accuracy, with XGBoost achieving the near-perfect score of 99.98%, showcasing their reliability in identifying and mitigating cyber threats. The analysis of data quality issues highlighted the importance of information cleanings and preprocessing stages as outlier removal, which improved the Dataset's reliability by eliminating approximately 40% of erroneous data. Maintaining high-quality healthcare data is essential for poor-quality information, incorrect diagnoses, biased healthcare results, and undermining the trust of AI systems.

5.2 Recommendations for Healthcare Systems

1. **Strengthen Cybersecurity Protocols**: Healthcare providers should adopt advanced machine-learning models to monitor network traffic and detect anomalies in real-time continuously. Incorporating models like XGBoost and Random-Forest reduces the likelihood of successful cyberattacks by identifying subtle network behavior irregularities.
2. **Implement Rigorous Data Quality Management**: Healthcare institutions must prioritize data governance; all patient data is accurate, consistent, and current. Routine data cleaning processes should be integrated with the missing values, outliers, and data standardization with sources such as electronic health records, laboratory results, and wearable devices.
3. **Adopt AI-Driven Monitoring Systems**: These AI tools for predictive maintenance and monitoring can help healthcare facilities identify equipment issues before they fail, optimize resource use, and improve patient outcomes. AI can also assist in preventing hospital readmissions by predicting patient risks early and providing timely interventions.
4. **Ensure Compliance with Regulations**: Healthcare governments must obey AI systems with file security rules such as HIPAA and GDPR. Regular audits and updates to safety procedures, including encryptions, multi-factor verification, and admittance control, are essential to safeguard sensitive patient data.

5.3 Role of Sustainable AI

Artificial intelligence influences sustainability within healthcare systems concerning resource efficacy and system longevity. AI improves healthcare delivery by mechanizing routine tasks, optimizing workflows, and reducing human error. Regarding Cybersecurity, AI can continuously protect healthcare data and reduce the risk of system downtimes due to cyberattacks [45]. AI supports data quality management with real-time data validation and cleaning; healthcare providers rely on accurate, actionable information. AI models improve their ability to adapt to evolving cyber threats and will further enhance the long-term sustainability of healthcare systems in securing patient data and maintaining trust in digital health technologies [46].

5.4 Future Work

There are many ways for upcoming studies to form based on the results of this reading. Exploring sophisticated machine-learning and deep-learning models, such as Neural Networks or ensemble techniques, could enhance the detection of complex and evolving cybersecurity threats. Techniques like unsupervised learning could be investigated for their potential to detect previously unknown vulnerabilities. The growing use of Internet-of-Things (IoT) devices and wearable health technologies introduces new cybersecurity challenges. Future research could focus on developing machine-learning models that secure these devices and data integrity while maintaining privacy standards. The AI schemes are more embedded in healthcare, and exploring the ethical inferences of AI-driven decision-making is crucial. The AI models do not introduce bias in underrepresented populations, which should be the priority for future studies.

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