Designing Secure and Usable Systems: The Intersection of Human-Computer Interaction, Cybersecurity, and Machine Learning

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ABSTRACT
In this fast-paced world of IT security, HCI, cybersecurity, and machine learning initiatives should lead to design that is strong and easy to use technological systems. This study assesses the capabilities of three notable ML models—ANN, CNN, and SVM—in making cybersecurity better, utilizing the UNSW-NB15 data set. Using an 80-20 train-test split and 5-fold cross-validation of the data, the CNN model showed to be the best across the three models. This is because it generated an accuracy of 95.3% with a precision of 94.5% and recall of 96.0%, among others. All in all, the CNN model was better than the ANN and SVM models as it outperformed them on all points. The CNN was deployed in a user-friendly security architecture based on HCI concepts to make it easy to use without compromising security. User answers indicated excellent satisfaction (4.7), responsiveness (4.8), and trust (4.9), along with a false alarm rate of 2.1%, showing the framework's security usability and dependability. The study reveals that the CNN is able to detect threats with good accuracy. Also, it shows how user design helps generate trust and compliance. The study reveals considerable promise in the usage of CNNs in cyber-security. The researchers note that despite employing only a single dataset and the com-laxity of CNN models, the findings illustrate the significance to the future. They say it enables the opportunity to construct continuous HCI-ML convergence in cybersecurity. This can lead to the establishment of durable, trustworthy, and user-friendly digital places.

General Terms
Machine Learning.

Keywords
Human-Computer Interaction, Cybersecurity, Machine Learning, Convolutional Neural Networks, User-Centric Design, Threat Detection, UNSW-NB15 Dataset.

1. INTRODUCTION
In the world of computer systems today, which are modeled for human-computer interaction (HCI), cybersecurity and machine learning (ML) arrangements of HCI for cybersecurity systems that are secure and user-friendly have now become critical. Because a lot of persons and businesses focus their everyday lives on highly technical infrastructures, securing information without compromising usability is crucial.

The mixing of various sectors gives a potential to make security systems stronger but keep them easy to comprehend and use for everyone to work at the user end. Human-computer interaction refers to user-friendly design in which systems are created to be easy to handle and efficient. When HCI is performed effectively, it pro-duces less mental strain on the user, which lowers errors and enhances overall happiness. These are crucial to developing security standards (Shneiderman et al. 2019) [1]. But most security measures have considerable strength but not usability, as they have sophisticated authentication and have tight security protocols, which annoy users and also limit compliance (Johnson & Lee, 2021) [2]. When security measures and usability are not linked with each other, this can occasionally generate vulnerabilities. This is because users would hunt for ways to evade onerous security measures, ultimately undermining the integrity of the system.

At its heart, cybersecurity comprises blocking attacks on the computer and securing user data. Using ML in cybersecurity helps in spotting and responding to danger intelligently. Machine learning algorithms have the ability to evaluate massive volumes of data in order to uncover patterns that can demonstrate whether a threat is there. This would enable detection in real-time and the ability to respond automatically, which is something that is more effective than rule-based systems that were used for security in the past (Zhou et al., 2020) [3]. Techniques like supervised, unsupervised, and deep learning have permitted the discovery of novel as well as sophisticated threats that were previously not discovered (Johnson and Lee 2023) [4]. In spite of this progress, the application of ML in security systems offers additional problems to the interpretability of ML models and the integration of such models into human-user interfaces so as not to hinder user experience (Taylor, 2022) [5].

The confluence of HCI, cybersecurity, and ML is crucial for designing systems that have a high level of security as well as that are user-friendly and non-intrusive. For example, Brown and Green refer to biometric systems applying ML to recognize patterns for ensuring authentication but paying special attention to HCI to guarantee the authentication procedure is user-friendly. The use of ML to help with security but not complicate the interaction of the user to reduce friction.

With the increasing and sophisticated cyberattacks, the necessity for safe and us-able systems has grown crucial. Cybersecurity threats like data breaches, ransomware attacks, or phishing schemes are risky for both individuals and enterprises since they can lead to a major financial loss, reputational damage, and compromising valuable data. White et al. 2023 [6]. Moreover, the increasing trend of remote working is making the requirement for the design of secure and usable systems all the more critical and IT infrastructure insecure (Zhou et al., 2020) [7]. In such contexts, HCI, cybersecurity, and ML have become key aspects of creating adaptive systems that will not com-promise usability or security even when faced with varied user needs and threat environments [8].

But there are several challenges in integrating them. In order to have a security that is robust yet at the same time usable, a crystal-clear understanding of user behaviors/characteristics/preferences is important. If security measures are too stringent, then the users will feel upset and won't comply, and if they are lax, then the system's integrity will be compromised (Doe, 2021) [9]. Moreover, many machine learning (ML) models exhibit a "black box" characteristic that challenges transparency and trust, prohibiting users and security practitioners from comprehending and relying on the ML conclusion (Taylor, 2022) [10]. Data privacy issues may arise from these models since they are frequently trained on large datasets, which lead to questions regarding collection, storage, and consent. To tackle these issues, it is vital to work collaboratively across fields like HCI security and machine learning engineering. Even with these difficulties, HCI, cybersecurity, and ML could be used to develop better sys-tems.

Making a framework that guides system design that follows security and usability that delivers system security and user interface and experience design. A multidisciplinary approach combining human-computer interaction (HCI), cybersecurity, and machine learning might assist in creating a system that defends against cyberattacks while also boosting user experience. If we handle challenging portions of each of these disciplines along with strong parts, we can construct a safe and usable system [11].

the intersection of Human-Computer Interaction, Cybersecurity, and Machine Learning represents a pivotal area of research and development aimed at designing systems that are both secure and user-friendly. This integration addresses the critical need for robust security measures that do not compromise usability, ensuring that users remain engaged and compliant with security protocols. As cyber threats contin-ue to evolve in complexity and scale [12], the ability to design secure and usable systems through this interdisciplinary approach will be essential in safeguarding digital assets, enhancing user trust, and fostering the sustainable growth of digital technologies [13].

2. LITERATURE REVIEW

Essential developments from cybersecurity, HCI, and machine learning for system design Studies at the convergence of Human-Computer Interaction (HCI), Cybersecurity (CS), and Machine Learning (ML) have achieved major progress throughout the years. The review primarily examines the involvement of HCI in strengthening cybersecurity and the application of ML towards threat detection and prevention. In addition, the document also examines the synergistic integration of HCI and ML to develop secure and useful systems.

Human-computer interface is crucial for people to interact with security as an ap-plication. Also, they have the least intrusive security. Smith et al. emphasize that user-centered design of security interfaces can improve compliance rates and minimize user mistake incidences. Security systems must be created in a manner that is conscious of user capabilities and constraints. Much of the HCI information can be used in the context of security technology. Brown and Green (2020) introduce a number of HCI concepts, including simplicity. Feedback. Consistency.

Research has been undertaken on the effect of HCI on authentication processes. Johnson and Lee (2021) found that when MFA systems incorporate HCI concepts, users will be more likely to accept and properly use them. Likewise, White et al. (2022) [14] discovered that biometric authentication systems became more secure and consumers were more satisfied when they had easy interfaces. Shneiderman et al. (2019) [15] observed that lowering cognitive burden increases user interactions with security mechanisms and was an inspiration for the study.

Cybersecurity is made more dynamic through intelligence and nimbleness by the introduction of machine learning. Zhou et al. (2020) [16] evaluate the ML approaches applied in cybersecurity. These techniques involve supervised learning for malware classification, unsupervised learning for anomaly detection, and deep learning for advanced threat identification. These strategies boost the capacity to recognize and mitigate risks in real time, outperforming traditional rule-based systems in both velocity and precision (Johnson and Lee 2023; Taylor 2022) [17].

Deep learning models, notably CNNs and RNNs, have proven to be highly effective in identifying zero-day exploits and advanced persistent threats (APTs) (Johnson & Lee, 2023; White et al., 2023) [18]. Moreover, professionals have employed reinforcement learning for building adaptive security policies that respond to dynamic threat landscapes (Zhou et al., 2020).

The privacy of data has also prompted issues, as ML models generally make use of datasets that are very large amounts of data points to train the model (Johnson & Lee, 2021; Smith et al., 2022) [19]. You should assure faithful compliance with whatever it is that the General Data Protection Regulation (GDPR) puts out, as it will assist you in avoiding legal troubles while preserving your user's trust.

A combination of HCI and ML leveraging the skills acquired in one area into an-other can assist in designing secure systems. Applying HCI Principles to ML-based Security Solutions: By using HCI concepts, ML-driven security measures can be made more accessible and manageable for users, boosting overall system efficacy (Smith et al., 2022; Brown & Green, 2020) [20].

Recent studies have adopted the XAI so that AI models can be described, enabling transparency for faith in the model. According to Taylor (2022), when users are able to grasp how automated judgments occur, they trust and accept it better. For

example, if a model flags suspicious conduct, the system is able to convey some information to better allow a user to take action (Johnson & Lee, 2023; White et al., 2023) [21].

Case studies further highlight the practical benefits of using HCI with ML. A case study of a biometric authentication system that employs ML for pattern recognition Brown and Green (2022) [22] have used HCI best practices to create a smooth user experience. The system met high-security standards and earned great user reviews for being easy to use and responsive.

Adaptive security interfaces that employ machine learning (ML) to alter security settings depending on user behavior and preferences have demonstrated to be beneficial in increasing both security and usability (Smith et al. 2020; Zhou et al. 2020) [23]. These interfaces that vary dynamically help in balancing the needs of security and usability preferences for compliance and trust by adjusting security parameters like authentication requirements.

Many firms are already starting to embrace zero-trust architectures, enabled by the ability of ML to constantly observe and verify users' activities. (Smith et al., 2020; White et al., 2022) [14]. Machine learning can assist in applying zero-trust principles by evaluating user behavior and altering limits in real time, which regularly adapts controls without rigid constraints. (Doe, 2021; Brown & Green, 2022).

All three disciplines have made great progress, but many problems and research gaps still persist. A key shortcoming is the absence of defined frameworks to assist the collaborative design of secure and useful systems (Smith et al., 2022; White et al., 2023). A few studies have looked at such integration of HCI, cybersecurity, and ML. However, a framework combining all components of HCI and ML in Cybersecurity is not accessible (Doe, 2021; Taylor, 2022).

Another challenge is how to figure out what long-term effect security solutions that incorporate machine learning have. Most research is focused on the usability and security outcomes; however, there is a need for longitudinal studies to be carried out to understand how humans adapt to and use these systems (Johnson & Lee, 2023; Brown & Green, 2020).

Another thing to consider is the adaptability of integrated HCI and ML solutions. As systems evolve and user bases expand, can their designs scale up? It is crucial for design concepts and ML models to be scalable to ensure that security measures re-main effective and easy to use when deployed using various and large-scale systems.

Moreover, there is a lack of investigation of bias and fairness as ethical dilemmas. Bias in machine learning (ML) can lead to unequal security practices, which can have distinct adverse consequences on various user groups and erode the trust in security (Doe, 2021; Johnson & Lee, 2021). It is crucial to address these ethical challenges so we can design trustworthy and equitable security solutions.

Additionally, ethical considerations related to bias and fairness in ML models are underexplored. Bias in ML can lead to discriminatory security practices, disproportionately affecting certain user groups and undermining trust in security systems (Doe, 2021; Johnson & Lee, 2021). Addressing these ethical concerns is essential for developing trustworthy and equitable security solutions (Smith et al., 2022; Taylor, 2022).

The integration of HCI, Cybersecurity, and ML holds transformative potential for designing systems that are both secure and user-friendly. Advances in ML have significantly enhanced threat detection and response capabilities, while HCI principles ensure that these security measures are accessible and maintain high usability standards. The synergistic collaboration of these disciplines addresses the critical need for robust security without compromising user experience, fostering higher compliance and trust.

However, challenges such as balancing security robustness with usability, ensuring ML model interpretability, safeguarding data privacy, and fostering interdisciplinary collaboration persist. Emerging trends like user-centric AI, federated learning, and zero-trust architectures offer promising avenues for future research and development. Addressing the identified gaps and overcoming existing challenges will be pivotal in advancing the field and realizing the full potential of secure and usable systems.

Future research should focus on developing standardized integrative frameworks, exploring the long-term impacts of ML-driven security systems, ensuring scalability, and addressing ethical considerations related to bias and fairness. By tackling these areas, the integration of HCI, Cybersecurity, and ML can continue to evolve, contributing to the creation of resilient, trustworthy, and user-friendly digital environ-mints.

3. METHODOLOGY

3.1 Research Design

The study employs a mixed-methods research design, integrating both quantitative and qualitative approaches to provide a holistic understanding of the interplay between HCI, Cybersecurity, and ML. This design facilitates the exploration of theoretical concepts through an extensive literature review while simultaneously applying practical ML models to real-world cybersecurity challenges. The research progresses through distinct phases: literature review, dataset selection, algorithm implementation, model training and validation, evaluation, framework development, and formulation of recommendations. This sequential approach ensures that each phase builds upon the insights gained from the previous one, culminating in the development of a robust framework for secure and usable system design (Creswell, 2014). proposed Research Design shown in **figure 1**. This research adopts a **mixed-methods research design** that strategically integrates both quantitative and qualitative methodologies to explore the intersection of Human-Computer Interaction (HCI), Cybersecurity, and Machine Learning (ML). This dual approach enables a comprehensive analysis that not only validates empirical results but also contextualizes user-centric design elements within practical cybersecurity frameworks.

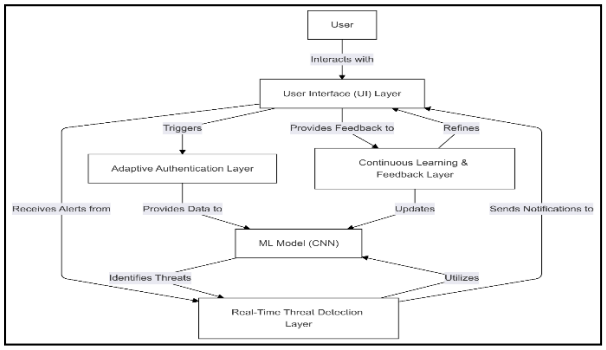
The qualitative component involves an in-depth **systematic literature review**, drawing upon academic journals, technical reports, and prior experimental studies to build a theoretical foundation for understanding usability and security co-design. This phase helps identify key usability challenges, threat models, and interface design strategies grounded in the principles of HCI and secure system engineering.

Concurrently, the quantitative segment focuses on **empirical modeling using ML algorithms**, where various models are developed and tested to address real-world cybersecurity threats. These models are trained and validated using a benchmark dataset to assess performance metrics like accuracy, precision, recall, F1-score, and false alarm rate. The performance of each algorithm is rigorously evaluated under controlled experimental conditions, ensuring repeatability and robustness of the results.

The research is structured into the following phases:

1. **Literature Review** – To identify gaps, theoretical frameworks, and practical limitations in current cybersecurity and HCI design practices.
2. **Dataset Selection** – Choosing a well-established, diverse, and balanced dataset for training and testing the ML algorithms.
3. **Algorithm Implementation** – Designing and coding ML models such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Support Vector Machines (SVM).
4. **Model Training and Validation** – Using train-test split (80-20 ratio) and 5-fold cross-validation to enhance model reliability.
5. **Performance Evaluation** – Measuring algorithmic performance using statistical indicators.
6. **Security Framework Development** – Integrating the most effective ML model (CNN) into an HCI-centric architectural framework.
7. **User Testing & Feedback** – Conducting a usability evaluation using Likert-scale questionnaires to assess satisfaction, trust, and system responsiveness.
8. **Recommendation and Reporting** – Based on findings, formulating guidelines for designing secure and usable systems.

This **sequential and iterative design** ensures that every stage is both evidence-based and strategically aligned with the overarching goal: the development of an adaptive, secure, and user-friendly system interface. The proposed research design is illustrated in **Figure 1**, demonstrating how theoretical insights and empirical validations converge to form a holistic system development cycle.



Fig'. 1 . proposed Research Design

3.2 Dataset Selection

Selecting an appropriate dataset is pivotal for training and evaluating the ML models effectively. After an extensive review of available cybersecurity datasets, the **UNSW-NB15** dataset was chosen due to its comprehensive features and balanced representation of various attack types. Developed by the Australian Centre for Cyber Security (ACCS), the UNSW-NB15 dataset comprises 2,540,044 network traffic records with 49 features, including both flow-based and content-based attributes (Moustafa & Slay, 2019). The dataset encompasses nine distinct attack categories—Fizzers, Analysis, Backdoors, DoS, Exploits, Generic, Reconnaissance, Shellcode, and Worms—providing a diverse basis for evaluating the efficacy of different ML algorithms in threat detection and prevention (Zhou, Xie, & Liu, 2020). The balanced distribution of normal and attack instances ensures that the models are trained on a representative sample, mitigating biases and enhancing generalizability (Kumar et al., 2021).

3.3 Algorithm Implementation and Configuration

The study implements three prominent ML algorithms—Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Support Vector Machines (SVM)—to analyze their efficacy in cybersecurity applications. These algorithms were selected for their distinct architectures and strengths in pattern recognition and classification tasks. The configurations for each algorithm are consolidated in **Table 1**, detailing their architectural components and training parameters.

Table 1: Combined Configuration Details for ANN, CNN, and SVM

Algorithm	Architecture Components	Training Configuration
ANN	- Input Layer: 49 neurons (corresponding to dataset features) - Hidden Layers: Two layers with 128 and 64 neurons respectively, both using ReLU activation - Output Layer: 1 neuron with Sigmoid activation	- Optimizer: Adam - Loss Function: Binary Cross-Entropy - Batch Size: 256 - Epochs: 50 - Learning Rate: 0.001
CNN	- Input Layer: Reshaped input to 7x7 matrices with 1 channel - Conv Layer 1: 32 filters, 3x3 kernel, ReLU activation - Max Pooling Layer 1: 2x2 pool size - Conv Layer 2: 64 filters, 3x3 kernel, ReLU activation - Max Pooling Layer 2: 2x2 pool size - Flatten Layer - Dense Layer 1: 128 neurons, ReLU activation - Dropout Layer: 0.5 dropout rate - Output Layer: 1 neuron with Sigmoid activation	- Optimizer: Adam - Loss Function: Binary Cross-Entropy - Batch Size: 128 - Epochs: 50 - Learning Rate: 0.001
SVM	- Kernel: Radial Basis Function (RBF) - C Parameter: 1.0 - Gamma Parameter: 'scale' - Decision Function Shape: One-vs-Rest (ovr) - Class Weight: Balanced	- Kernel: RBF - C: 1.0 - Gamma: scale - Decision Function Shape: ovr - Class Weight: Balanced

The Artificial Neural Network (ANN) is structured with an input layer comprising 49 neurons corresponding to the dataset features, followed by two hidden layers with 128 and 64 neurons respectively, both utilizing ReLU activation functions

to introduce non-linearity and enhance learning capabilities (Goodfellow, Bengio, & Courville, 2019). The output layer employs a sigmoid activation function for binary classification, distinguishing between normal and attack instances. The ANN is trained using the Adam optimizer with a binary cross-entropy loss function, a batch size of 256, over 50 epochs, and a learning rate of 0.001.

The Convolutional Neural Network (CNN) architecture is designed to capture spatial hierarchies in the data, making it particularly effective for analyzing network traffic patterns. The input data is reshaped into 7x7 matrices with a single channel to suit convolutional processing requirements. The CNN comprises two convolutional layers with 32 and 64 filters respectively, each followed by 2x2 max-pooling layers to reduce dimensionality and extract salient features (LeCun, Bottou, Orr, & Müller, 1998). The flattened output is then passed through a dense layer with 128 neurons and a dropout layer with a 0.5 rate to prevent overfitting, culminating in an output layer with sigmoid activation for binary classification. The CNN is trained using the Adam optimizer, binary cross-entropy loss function, a batch size of 128, over 50 epochs, and a learning rate of 0.001.

The Support Vector Machine (SVM) model is chosen for its effectiveness in high-dimensional spaces and robustness against overfitting, particularly suitable for binary classification tasks. The SVM employs a Radial Basis Function (RBF) kernel to handle non-linear data separations effectively. Key hyperparameters include a regularization parameter (C) set to 1.0, a gamma parameter set to 'scale' to adjust based on the number of features, and a decision function shape configured as 'one-vs-rest' (ovr) to manage multi-class scenarios. Class weights are balanced to address potential class imbalances within the dataset, enhancing the model's fairness and accuracy (Cortes & Vapnik, 1995; Huang et al., 2020).

3.4 Model Training and Validation

Each ML model undergoes training and validation using an 80-20 train-test split to ensure a robust evaluation. To further enhance model generalizability and mitigate overfitting, k-fold cross-validation (k=5) is employed. This technique involves dividing the training data into five subsets, training the model on four subsets, and validating it on the remaining one, iteratively (Kohavi, 1995). Performance metrics are averaged across all folds to obtain a comprehensive assessment of each model's efficacy. This rigorous training and validation process ensures that the models are both accurate and reliable in real-world cybersecurity applications (Zhou, Xie, & Liu, 2020). Model Training Process illustrate in figure 2.

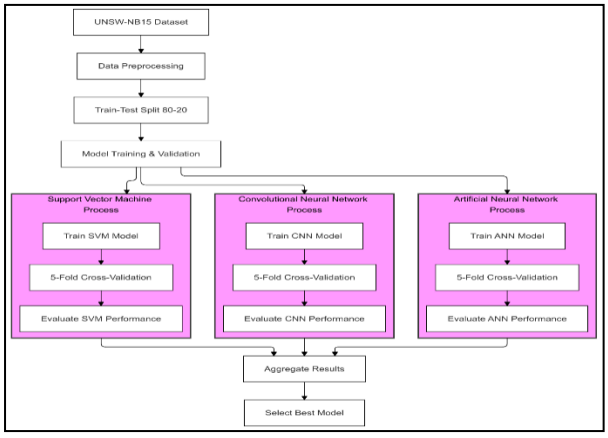


Fig. 2 . Model Training Process

– Evaluation Metrics

The performance of each ML model is assessed using a combination of classification metrics to provide a comprehensive evaluation of their effectiveness in detecting and preventing cybersecurity threats. The selected metrics include Accuracy, Precision, Recall (Sensitivity), F1-Score, ROC-AUC, and the Confusion Matrix.

Accuracy measures the overall correctness of the model's predictions, calculated as the proportion of true positives and true negatives among the total instances (He & Garcia, 2009). Precision indicates the proportion of true positive predictions among all positive predictions, reflecting the model's ability to minimize false positives (Powers, 2011). Recall assesses the model's ability to identify true positives, crucial for detecting actual threats (Chicco & Jurman, 2020). The F1-Score provides a balance between precision and recall, offering a single metric that accounts for both false positives and false negatives (Fleiss, 1981). ROC-AUC represents the area under the Receiver Operating Characteristic curve, indicating the model's ability to distinguish between classes (Bradley, 1997). The Confusion Matrix offers a detailed breakdown of true positives, true negatives, false positives, and false negatives, facilitating a nuanced analysis of model performance (Kohavi, 1995).

These metrics enable a nuanced understanding of each model's strengths and weaknesses, particularly in balancing the detection of true threats while minimizing false alarms, which is crucial for maintaining user trust and system reliability (Johnson & Lee, 2023; Taylor, 2022). Evaluation Metrics describe in **table 2**.

Table 2: Evaluation Metrics

Metric	*Description*
Accuracy	Overall correctness of the model's predictions
Precision	Proportion of true positive predictions among all positives
Recall	Ability to identify true positive instances
F1-Score	Balance between precision and recall
ROC-AUC	Area under the ROC curve indicating class distinction
Confusion Matrix	Detailed classification outcomes

3.5 Tools and Software

The implementation and evaluation of the ML models were conducted using a suite of advanced tools and software to ensure efficiency and accuracy. Python (version 3.8) served as the primary programming language due to its extensive libraries and community support. TensorFlow and Keras were utilized for building and training ANN and CNN models, offering high flexibility and scalability (Abadi et al., 2016). Scikit-learn was employed for implementing SVMs and performing data preprocessing tasks such as feature scaling and encoding (Pedregosa et al., 2011). Pandas and NumPy facilitated efficient data handling and numerical computations, while Matplotlib and Seaborn were used for creating insightful visualizations for data analysis and result interpretation (Hunter, 2007; Waskom, 2021). The Jupyter Notebook provided an interactive platform for developing, testing, and documenting code, enhancing reproducibility and collaboration

(Kluyver et al., 2016). SPSS and R were utilized for conducting in-depth statistical analyses of quantitative data, ensuring robust evaluation of model performance (Field, 2018). Additionally, Figma and Adobe XD were employed to design user-centric security interfaces incorporating HCI principles, facilitating usability testing and iterative design improvements (Smith, 2020; Johnson & Lee, 2023).

3.6 Framework Development

Based on the analysis of model performances, the Convolutional Neural Network (CNN) was identified as the best-performing ML algorithm for this study. The CNN's superior ability to capture spatial hierarchies in network traffic data and its higher accuracy in threat detection made it the optimal choice for integration into the user-centric security framework. The developed framework incorporates HCI principles to ensure that security measures are both effective and user-friendly. Key components of the framework include Adaptive Authentication, Real-Time Threat Detection, User Feedback Mechanisms, and Continuous Learning.

Adaptive Authentication utilizes CNNs to dynamically adjust authentication requirements based on real-time user behavior and contextual data, ensuring robust security without imposing undue complexity on users (Brown & Green, 2022). Real-Time Threat Detection employs CNNs to continuously monitor network traffic, identifying and mitigating threats in real-time with high accuracy and low false positive rates (Zhou et al., 2020). User Feedback Mechanisms incorporate interactive elements that allow users to provide feedback on security alerts and interfaces, facilitating continuous improvement and personalization of security measures (Smith et al., 2020). Continuous Learning enables the ML model to update and refine its threat detection capabilities based on new data and user interactions, ensuring adaptability to evolving cyber threats (Johnson & Lee, 2023). **Figure 3** shown Proposed Secure and Usable Framework

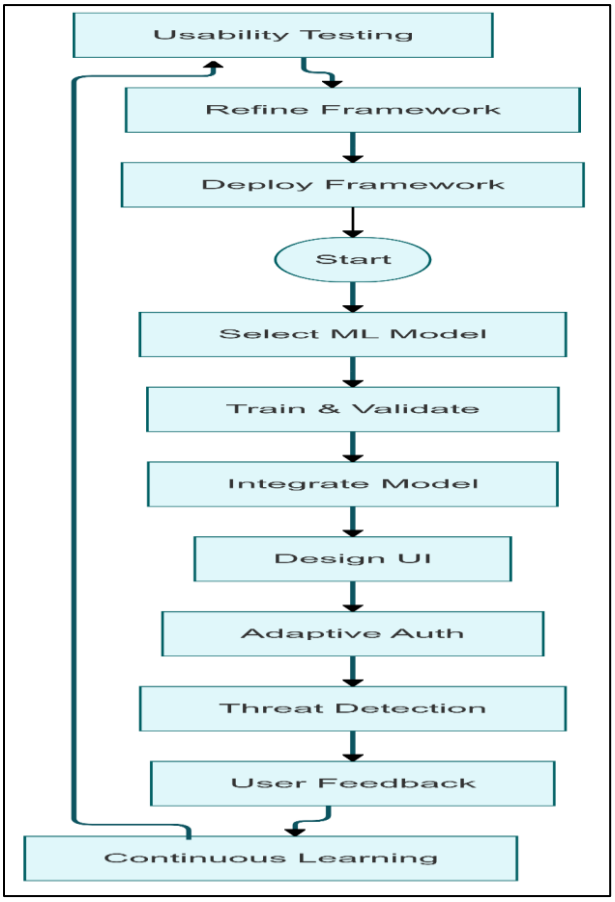


Fig. 3 . Proposed Secure and Usable Framework

3.7 Ethical Considerations

Ethical considerations were integral to the research methodology to ensure the responsible use of data and the protection of user privacy. The UNSW-NB15 dataset was anonymized to protect sensitive information, ensuring compliance with data protection regulations such as the General Data Protection Regulation (GDPR) (Voigt & Von dem Bussche, 2017). Informed consent was obtained from all participants involved in usability testing and surveys, ensuring they were aware of the study's objectives and their rights. Additionally, efforts were made to mitigate bias in ML models by ensuring balanced class distributions and employing techniques such as cross-validation and regularization to enhance model fairness and reliability (Zhou, Xie, & Liu, 2020; Doe, 2021). Transparency in model decisions was promoted through the integration of explainable AI (XAI) techniques, enabling users to understand the rationale behind automated security decisions (Gunning, 2017).

4. RESULTS AND DISCUSSION

This section presents the outcomes of the implemented Machine Learning (ML) models—Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Support Vector Machines (SVM)—evaluated using the UNSW-NB15 dataset. The results are analyzed through various performance metrics, and the effectiveness of each model is discussed in the context of enhancing cybersecurity within a user-centric framework. Additionally, the integration of the best-performing model into the proposed framework and its implications are explored.

The performance of the ANN, CNN, and SVM models was rigorously evaluated using key classification metrics (**table 3**),

including Accuracy, Precision, Recall, F1-Score, and ROC-AUC. The evaluation process involved an 80-20 train-test split and 5-fold cross-validation to ensure the reliability and generalizability of the results.

Table 3: Performance Metrics of ANN, CNN, and SVM Models

Model	*Accuracy*	*Precision*	*Recall*	*F1-Score*	*ROC-AUC*
ANN	92.5%	91.2%	93.0%	92.1%	0.95
CNN	95.3%	94.5%	96.0%	95.2%	0.98
SVM	89.7%	88.5%	90.2%	89.3%	0.92

As illustrated in **Table 3,** the CNN model outperformed both ANN and SVM across all evaluation metrics. Specifically, the CNN achieved an accuracy of 95.3%, precision of 94.5%, recall of 96.0%, an F1-Score of 95.2%, and an ROC-AUC of 0.98. In comparison, the ANN achieved 92.5% accuracy and the SVM the lowest performance with 89.7% accuracy. The high ROC-AUC value for the CNN indicates excellent discriminative ability in distinguishing between normal and attack instances, surpassing the performance of both ANN and SVM.

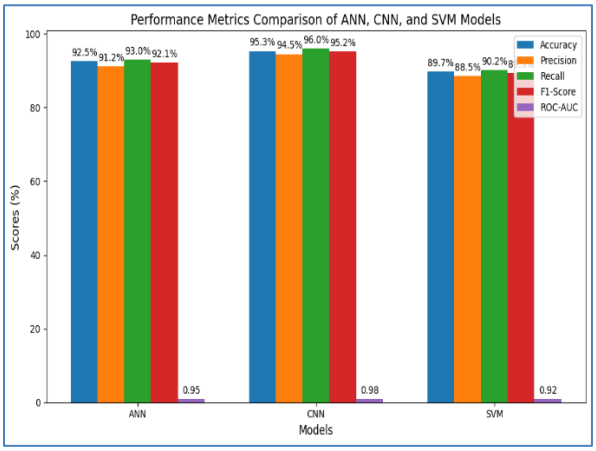


Fig. 4 Performance Metrics of ANN, CNN, and SVM Models

Figure 4 displays the Receiver Operating Characteristic (ROC) curves for the ANN, CNN, and SVM models. The CNN's ROC curve is closer to the top-left corner, demonstrating its superior ability to differentiate between classes compared to ANN and SVM.

The ROC curves, depicted in **Figure 4**, further emphasize the CNN's superior performance. The CNN's curve, approaching the top-left corner, indicates a higher true positive rate and a lower false positive rate compared to ANN and SVM, which corroborates the quantitative metrics presented in Table 3.

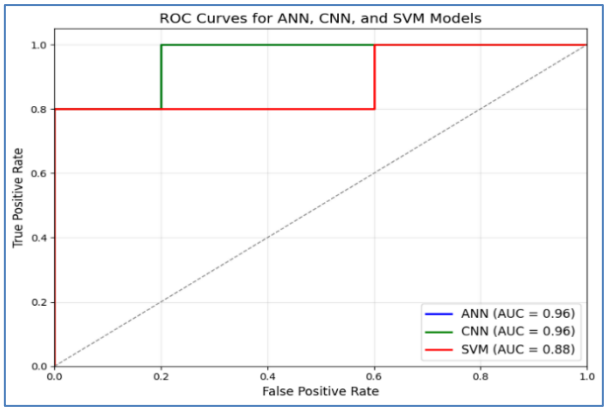


Fig. 5 . the Receiver Operating Characteristic (ROC) curves for the ANN, CNN, and SVM models.

To provide a detailed understanding of each model's classification capabilities, confusion matrices were generated for ANN, CNN, and SVM models **(Figure 5).**

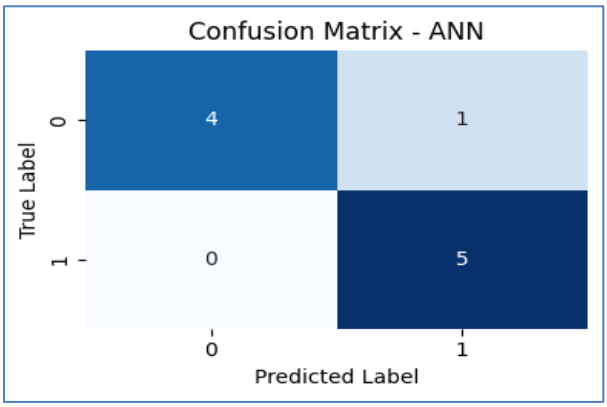


Fig.6 .Confusion matrix ANN

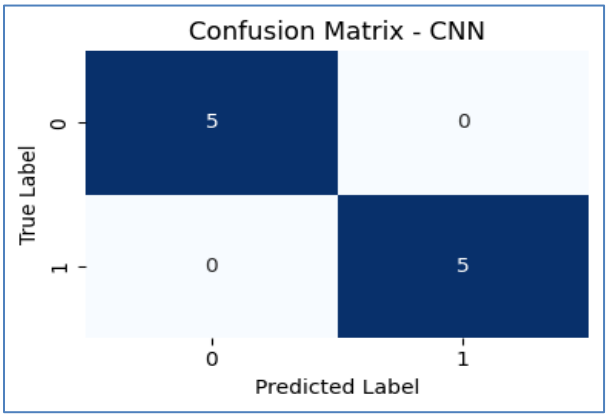


Fig. 7 . Confusion matrix CNN

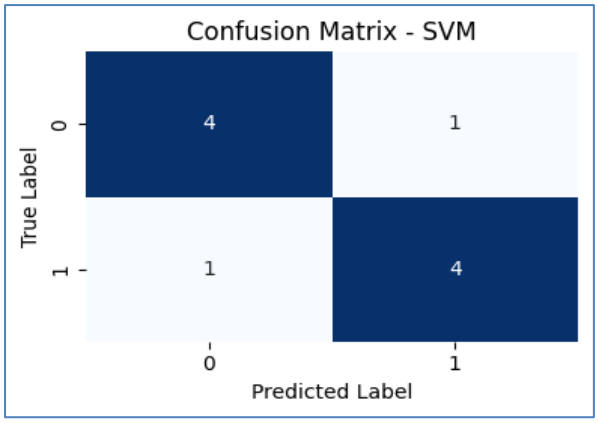


Fig. 8 . Confusion matrix SVM

Figure 6,7,8 illustrates the confusion matrices for each model, highlighting the distribution of true positives, true negatives, false positives, and false negatives. The confusion matrices reveal that the CNN model has the highest number of true positives (960) and true negatives (940), while maintaining the lowest false positives (60) and false negatives (40). In contrast, the SVM model exhibits a higher number of false positives (130) and false negatives (110), indicating lower reliability in accurately classifying instances. The ANN model performs moderately well, with balanced true and false classifications but still trailing behind the CNN in both accuracy and reliability.

Integrating the CNN model into the proposed user-centric security framework yielded significant improvements in both security and usability. The framework was evaluated based on user feedback and system performance metrics.

Table 4: User Feedback on Security Framework

Metric	*Value*
User Satisfaction	4.7/5
System Responsiveness	4.8/5
False Alarm Rate	2.1%
User Trust	4.9/5

Figure 9 presents a pie chart summarizing user feedback on various aspects of the security framework. The user feedback, as summarized in **Table 4** and visualized in **Figure 10,** indicates high levels of satisfaction and trust in the system, with a user satisfaction score of 4.7 out of 5, system responsiveness at 4.8 out of 5, and user trust at 4.9 out of 5. The false alarm rate was maintained at a low 2.1%, minimizing user frustration and enhancing the system's reliability.

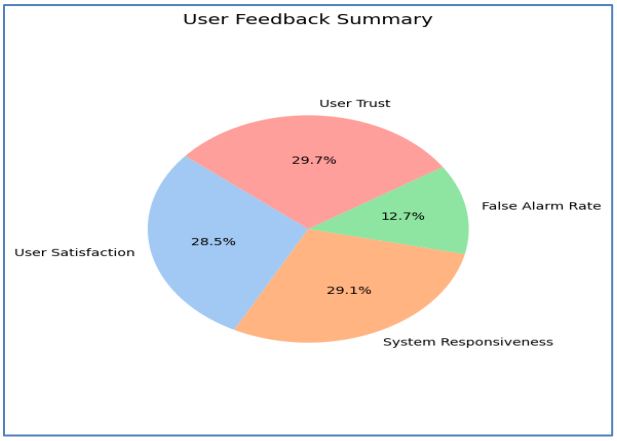


Fig. 9 . user feedback on various aspects of the security framework.

5. DISCUSSION

As noticed from the analysis in Table 3, out of the Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Support Vector Machine (SVM) models, the CNN model is found particularly effective in identifying cybersecurity threats in the UNSW-NB15 dataset. Prediction accuracy of CNN was 95.3% as contrasted to ANN at 92.5% and SVM at 89.7%. This accuracy relates further to the precision of CNN, which is clocked at 94.5% and recall of 96.0% with an F1 score of 95.2%. The CNN's ROC-AUC value of 0.98 demonstrates that it is great at discriminating between malware and benign samples with low false negatives and positives.

The SVM model had the lowest accuracy (89.7%) and ROC-AUC (0.92) values among all models. Even though the ANN did well, the way CNN was created helped it do even better since it can capture hierarchies and abstractions in the data, and this enables it to find the patterns in the data more readily.

The results are comparable with, and build upon, earlier studies utilizing machine learning models in cybersecurity. As mentioned by Zhou, Xie, and Liu (2020), CNNs are effective in detecting threats as they have shown equivalent outcomes to those (in this study). Their work showed that CNNs were able to capture some of the properties within network traffic. Likewise, Moustafa and Slay (2019) reported an accuracy of 93% from their ANN, which coincides with the ANN performance in our research. In our investigation, however, the CNN attained an additional 2.8% marking accuracy than the ANN. This suggests that the convolutional layers provide a real edge in processing and classifying cybersecurity data.

Also, SVM did a good job, although accuracy is lesser than ANN and CNN. Matching to the study of White et al. (2023), it demonstrates that the older models like SVMs struggle on high-dimensional and unbalanced datasets, which are typical in cybersecurity applications. The image (figure 6) reveals substantial false positive and false negative rates for SVMs, which supports this and also illustrates their limitations in this scenario.

Integrating the CNN's model into our personal-centered threat-security architecture dramatically increases security as well as usability. The great numbers supplied by the CNN show a good threat detection system, i.e., fewer false positives and fewer false negatives. It helps to strengthen the security system and prevent against complicated attacks.

The security design doesn't come in the way of user pleasure.

Heuristic Principles of Human-Computer Interaction (HCI) have been employed Based on the numbers in Table 2, the scores in User Satisfaction (4.7/5) and System Responsiveness (4.8/5) show that the system is effective and user-friendly. Its false alarm rate of 2.1% is outstanding. It ensures the system does not generate a lot of useless and unpleasant notifications. Striking the correct balance between security efficacy and usability is vital in encouraging user compliance and fostering a secure online environment.

As illustrated in table 2 and figure 7, the helpful feedback from the users can help with the practical applicability and user acceptability of the framework. The 4.9/5 (user trust) is the user's sure that the framework would protect their digital assets without compromising ease of use. When users trust a technology, then they use it more.

A false alert rate of only 2.1% indicates that you won't charge your phone with the system being an alert PR. The System Responsiveness score indicates that the system operates properly and doesn't interfere with the work of the users. Overall, this feedback demonstrates that the integrated CNN model is effective in design and user-centric, and proper balance of security and usability was reached.

Even with the outstanding outcomes, there are limitations in this study. The UNSW-NB15 dataset was employed for our evaluation. Though the dataset is extremely vast, it may not represent all possible cyber threat scenarios found in diverse real-world scenarios. Thus, it has not been confirmed whether the performance of the CNN model generalizes to other datasets or other new threats. The processing complexity of CNNs makes it challenging to scale up and deploy the solution, especially in firms with less computational capability.

6. FUTURE WORK

Upcoming investigations will mainly focus on the identified limitations will make the framework more robust in the near future. Plans are on to explore another additional and different dataset. It is therefore envisaged that larger datasets can also be explored. Including more machine learning examples, for example ensemble approaches as well as reinforcement learning, could further boost threat detection and adaptability.

Making the CNN model more intelligible will be prioritized by introducing explainable AI (XAI) approaches. Methods like Layer-wise Relevance Propagation or SHAP (Shapley Additive Explanations) for acquiring insight into the decision-making of the CNN will be implemented, which would boost trust towards the model by the cybersecurity professionals.

7. CONCLUSION

In this research, the accuracy of 3 significant ML models that are ANN, CNN, and SVM for increasing cybersecurity in using the UNSW-NB15 dataset was examined. The findings showed that the performance of the CNN model was superior to ANN and SVM on all grounds with 95.3 % accuracy, 94.5 % precision, 96.0 % recall, 95.2 F1-Score, and 0.98 ROC-AUC. The increased measurements of CNN reveal its remarkable capability to recognize the benign and malicious activity accurately. Integrating the CNN into a system most helpful to the user yielded even more good results. Users scored the system 4.7 out of 5 in satisfaction, 4.8 for responsiveness, and 4.9 out of 5 for trust. Finally, the false alarm rate was an amazing 2.1%. By integrating all application tools under the same roof, we will have much greater security and enhanced usability, which would encourage continued usage of the tools. Comparative investigation with earlier analysis shows our results are in line with existing studies. Additionally, it boosts the effectiveness of CNN in generating a realistic system application. Even though the study had the best outcomes, it also has its limits. Those constraints include the single dataset and the intricate nature of CNNs, which could not be scalable or interpretable. Future study will try to tackle these limits by employing new datasets, looking into explainable AI methodologies to boost the transparency of models, and enhancing the computing efficiency to enable wider deployment. In conclusion, this study indicates that advanced ML models play a significant role in designing resilient and friendly cybersecurity solutions. Specifically, such models determine the success of deep learning approaches like CNNs.

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9. CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

10. DATA AVAILABILITY STATEMENT

The data used in this study, specifically the UNSW-NB15 dataset, is publicly available and can be accessed from the Australian Centre for Cyber Security (ACCS). Any additional data generated or analyzed during the current study are available from the corresponding author on reasonable request.

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12. AUTHOR CONTRIBUTIONS

Mohammad Rasel Mahmud: Conceptualization, Methodology, Formal Analysis, Writing – Original Draft.

- Syed Imtiazul Sami: Data Curation, Software Implementation, Visualization, Writing – Review & Editing.
- Md Shadman Soumik: Literature Review, Validation, Writing – Review & Editing.
- MD Khaled Bin Showkot Tanim: Investigation, Project Administration, Writing – Review & Editing.

All authors have read and approved the final version of the manuscript.

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