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ENSEMBLE METHOD USING FACENET AND CNN FOR FACE RECONGNITION

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Abstract

Face recognition has become a vital application in the domains of computer vision and biometric identification, playing a crucial role in security, authentication, and surveillance systems. This research focuses on the development and evaluation of a face recognition system using deep learning, specifically comparing the performance of a traditional Convolutional Neural Network (CNN), the FaceNet architecture, and a hybrid ensemble model that integrates both. The objective was to assess each model's effectiveness, accuracy, and generalization capability in recognizing human.. All models were trained using a facial image dataset and evaluated across ten epochs using standard

Keywords: Face Recognition, Deep Learning, Computer Vision, Convolutional Neural Network (CNN), FaceNet, Ensemble Model.

INTRODUCTION

Face recognition has emerged as one of the most prominent applications of computer vision and artificial intelligence, with its roots tracing back to the 1960s when researchers began exploring pattern recognition techniques (Li, 2022). Over the decades, advancements in machine learning and deep learning have revolutionized the field, enabling systems to achieve unprecedented accuracy and robustness. Today, face recognition is widely used in various domains, including security, healthcare, and human-computer interaction, due to its ability to identify individuals quickly and efficiently (Sharma et al., 2021).

However, the COVID-19 pandemic introduced new challenges, such as the widespread use of face masks, which occlude significant portions of the face. Traditional face recognition systems, which rely on full facial features, struggled to

performance metrics such as accuracy and loss. The CNN model achieved a peak accuracy of 94.69% but exhibited inconsistent learning and signs of overfitting. FaceNet performed with greater stability, reaching a peak accuracy of 97.43% and maintaining low loss values throughout training. The ensemble model, which combines outputs from CNN and FaceNet, surpassed both, achieving the highest peak accuracy of 98.20% and the lowest final loss. In practical evaluation, the ensemble successfully identified a known individual and accurately inferred demographic features such as gender and age range. The results demonstrate that combining models into an ensemble yields even greater performance, making it the most suitable approach for real-world face recognition applications.

adapt to this new reality (Sethi et al., 2021). Additionally, low-light conditions and crowded environments further complicate the task of accurate face recognition. To address these challenges, researchers have turned to advanced deep learning techniques, including self-supervised learning and hybrid models, to improve the robustness of face recognition systems (Loey et al., 2021; Ohri and Kumar, 2021).

The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly enhanced the performance of face recognition systems. CNNs excel at extracting hierarchical features from images, making them ideal for tasks such as face detection, feature extraction, and classification (Srivastava et al., 2021). State-of-the-art algorithms, such as FaceNet, DeepFace, and ArcFace, leverage deep learning to achieve near-human accuracy in face recognition tasks (Hariri, 2022). These algorithms have been instrumental in addressing challenges such as variations in pose, lighting, and facial expressions.

Despite these advancements, CNN-based models often struggle with overfitting and inconsistent generalization across diverse datasets, while FaceNet, though more stable, may not fully capture discriminative features in complex, unconstrained environments. As a result, existing systems are still prone to performance drops when applied in real-world scenarios characterized by occlusion, lighting variation, and diverse facial expressions (Srivastava et al., 2021; Teoh et al., 2021).

This study aims to address these gaps by developing and evaluating an ensemble model that integrates CNN and FaceNet architectures for face recognition. The goal is to determine whether combining the strengths of both models can improve accuracy, stability, and generalization compared to using CNN or FaceNet alone. By doing so, the research seeks to provide a more robust solution for real-world applications such as surveillance, authentication, and biometric security.

LITERATURE REVIEW

Researchers have proposed various solutions to address the challenges in face recognition. Early approaches focused on improving feature extraction and classification techniques. For example, Eigenfaces and Fisherfaces used Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) to reduce dimensionality and improve recognition accuracy (Srivastava et al., 2021). However, these methods were limited by their inability to handle non-linear variations and occlusions.

With the rise of deep learning, CNNs became the dominant approach for face recognition. State-of-the-art algorithms such as FaceNet, DeepFace, and ArcFace leverage deep neural networks to achieve near-human accuracy (Hariri, 2022). FaceNet, for instance, uses a triplet loss function to learn discriminative features, while ArcFace introduces additive angular margin loss to enhance feature separability. These methods have significantly improved performance in controlled environments but still face challenges in real-world scenarios.

To address the issue of masked faces, researchers have proposed hybrid models that combine CNNs with traditional machine learning techniques. For example, Loey et al. (2021) developed a hybrid deep transfer learning model for mask detection, achieving high accuracy in identifying masked individuals. Similarly, Sethi et al. (2021) proposed a CNN-based approach for mask detection, which was trained on a diverse dataset to improve robustness.

For low-light conditions, techniques such as image enhancement and generative adversarial networks (GANs) have been employed to improve visibility and feature extraction. Sharma et al. (2021) highlighted the use of GANs to generate synthetic data for training face recognition systems, enabling them to perform better in challenging lighting conditions.

The current trend in face recognition research focuses on improving robustness and generalizability in real-world scenarios. State-of-the-art algorithms such as FaceNet, ArcFace, and DeepFace continue to dominate the field, with ongoing efforts to enhance their performance in challenging conditions (Hariri, 2022). Researchers are increasingly exploring self-supervised learning techniques, which reduce the reliance on labeled data and improve the model's ability to learn from unlabeled datasets (Ohri & Kumar, 2021).

Another emerging trend is the use of hybrid models that combine deep learning with traditional machine learning techniques. For example, Loey et al. (2021) proposed a hybrid model for mask detection that integrates CNNs with transfer learning, achieving state-of-the-art performance. Similarly, GANs are being used to generate synthetic data for training, enabling models to generalize better to unseen conditions (Sharma et al., 2021).

Efforts are also being made to optimize face recognition systems for real-time performance and resource-constrained environments. Lightweight CNN architectures, such as MobileNet and EfficientNet, are being adopted to reduce computational overhead while maintaining high accuracy (Srivastava et al., 2021).

Despite the significant progress made in face recognition research, several areas require further improvement. First, the performance of existing systems in low-light conditions and crowded environments remains suboptimal. While techniques such as image enhancement and GANs have shown promise, there is a need for more robust solutions that can handle extreme variations in lighting and occlusion.

This paper aims to address these gaps by developing a face recognition system that leverages state-of-the-art algorithms and CNN architectures to improve robustness in challenging scenarios. By integrating techniques such as self-supervised learning, hybrid models, and image enhancement, the proposed system seeks to deliver high accuracy and reliability in real-world applications.

METHODOLOGY

The methodology encompasses **Data Acquisition**, **Data Preprocessing**, **Model Architecture Design**, and **Model Evaluation**. The overall architecture of the proposed face recognition system is illustrated in **Figure 1**, which provides a high-level overview of the key components and their interactions. The system employs a hybrid ensemble approach that combines a **Convolutional Neural Network (CNN)** and the **FaceNet** model for robust feature extraction, followed by **weighted average feature fusion** to generate the final prediction.

As shown in Figure 1, the pipeline begins with an input face image, which undergoes preprocessing steps such as normalization and resizing. The preprocessed image is then passed through two parallel streams: one using the **FaceNet model** for deep feature embedding and the other using a **CNN model** for convolutional feature extraction. Feature vectors generated from both models are subsequently fused using a **weighted averaging technique**, producing a more discriminative and generalized representation. The fused features are then used to make the final identity prediction.Each component of this methodology is elaborated upon in the subsequent sections.

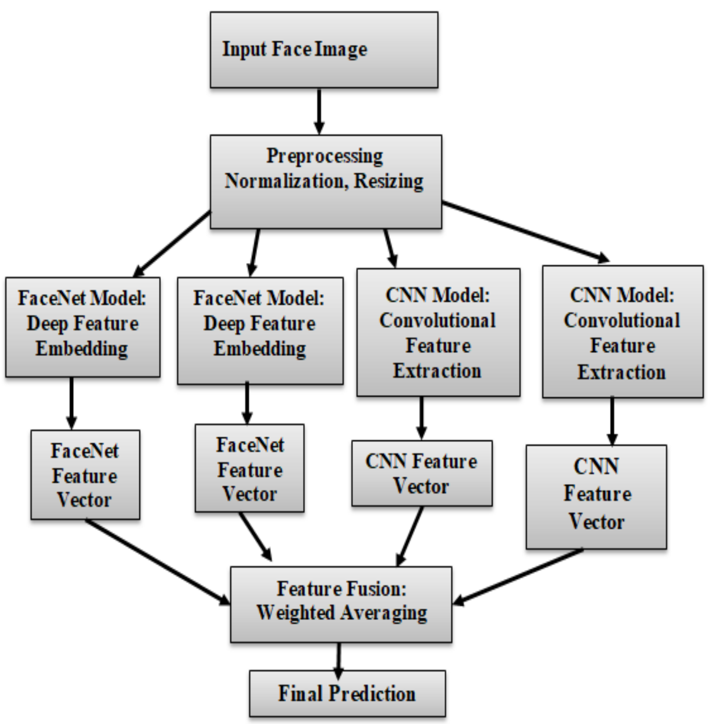

Figure 1 Model Architecture

Data Acquisition

For this project, the Labeled Faces in the Wild (LFW) dataset was utilized. The LFW dataset is a benchmark dataset in face recognition research, comprising over 13,000 images of faces collected from the web. Each image is labeled with the name of the person pictured. Only individuals with at least 70 distinct images are included to ensure sufficient representation and class balance.

Key characteristics of the dataset include:

i. **Image resolution**: Reduced to 50×37 pixels to optimize computational efficiency.

ii. **Color scale**: Grayscale format was used to simplify model complexity and focus on structural features.
iii. **Number of subjects**: Approximately 7 classes (persons) with a substantial number of images per class.
iv. **Use case relevance**: The dataset presents real-world challenges such as variations in pose, lighting, and facial expression, making it ideal for evaluating deep learning models in face recognition tasks.

The selection of this dataset is grounded in its widespread use, comprehensive annotations, and suitability for training CNN-based models.

Data Preprocessing

Data preprocessing plays a crucial role in the success of any machine learning pipeline. The following preprocessing steps were applied:

I. **Normalization**: All pixel values of the images were normalized to the range [0, 1]. This step ensures that the neural network converges faster by stabilizing gradients during training.
II. **Reshaping**: Since the original images are two-dimensional grayscale, an additional channel dimension was appended to match the input requirements of CNN layers, which expect three-dimensional data.
III. **Label Encoding**: The target labels (i.e., person IDs) were transformed into one-hot encoded vectors, enabling multi-class classification. This approach is essential for using softmax activation in the final output layer.
IV. **Data Quality Assurance**: Images were visually inspected to ensure clarity and consistency, and those that did not meet quality standards (if any) were excluded.

Preprocessing ensures that the input data is clean, consistent, and properly formatted, ultimately improving model performance. To evaluate the generalization ability of the model, the preprocessed dataset was partitioned into two subsets:

I. **Training Set (80%)**: Used for model learning, where the network parameters are optimized.
II. **Testing Set (20%)**: Used to evaluate model performance on unseen data.

A random seed was used to ensure reproducibility of results during the splitting process. This stratification is essential in machine learning to prevent overfitting and to assess how well the model performs in real-world scenarios.

Model Architecture Design

The model architecture is a deep **Convolutional Neural Network (CNN)**, a class of deep learning models particularly well-suited for image classification tasks. The design is informed by best practices in CNN design and tailored specifically for facial feature extraction and classification. The **architectural components are:**

I. **Convolutional Layers**: These layers apply multiple filters to the input image to detect features such as edges, textures, and facial landmarks. Multiple convolutional layers with increasing filter depth allow the network to learn hierarchical features.

II. **Max-Pooling Layers**: Following each convolutional layer, max-pooling is used to reduce the spatial dimensions of the feature maps, minimizing overfitting and reducing computational load.

III. **Flattening Layer**: Converts the multidimensional feature maps into a one-dimensional vector that can be fed into fully connected layers.

IV. **Dense (Fully Connected) Layers**: These layers perform high-level reasoning based on the features extracted by the convolutional layers.

V. **Dropout Layer**: Dropout is applied to the dense layer to mitigate overfitting by randomly deactivating neurons during training.

VI. **Output Layer**: A softmax activation function is used in the final layer to classify the input image into one of the predefined facial identity classes.

This architectural design balances depth and computational efficiency, making it appropriate for training on a mid-sized dataset such as LFW. Model Training Configuration are:

I. **Optimizer**: The **Adam optimizer** was selected for its adaptive learning rate capabilities and overall efficiency. Adam combines the advantages of RMSprop and SGD with momentum, making it well-suited for non-stationary objectives.

II. **Loss Function**: **Categorical Crossentropy** was used, which is standard for multi-class classification tasks. It quantifies the difference between the predicted probability distribution and the true distribution.

III. **Metrics**: **Accuracy** was used as the primary evaluation metric during training to monitor the percentage of correctly classified instances.

These choices ensure a stable and efficient training process, enabling the model to converge to an optimal solution within a reasonable number of epochs.

Evaluation

Model Training and Validation

Training involved feeding the model with the training dataset over a series of iterations (epochs). The key parameters for training include:

I. **Epochs**: 10 complete passes over the training data were performed. This number was chosen to balance learning progression with the risk of overfitting.

II. **Batch Size**: A batch size of 32 was used, allowing efficient computation and stable gradient updates.

III. **Validation Set**: The testing subset was used as a validation set to monitor the model's performance after each epoch and detect any signs of overfitting early.

During training, both training accuracy and loss, as well as validation accuracy and loss, were tracked to understand the model's learning dynamics. After training, the model was evaluated using the testing dataset to measure its effectiveness.

Visualization of Results

To enhance interpretability and provide visual insights into the model's learning behavior, several graphical representations were employed:

I. **Training History Plots**: Line graphs depicting accuracy and loss for both training and validation sets across epochs, helping to diagnose underfitting or overfitting.
II. **Performance Metric Charts**: Bar charts representing the final values of accuracy, precision, recall, and F1-score, offering a visual summary of the model's effectiveness.
III. **Sample Image Predictions**: Display of randomly selected test images along with their predicted and actual labels, demonstrating the real-world application of the model.

These visual tools aid in communicating findings clearly and provide an intuitive understanding of the system's strengths and limitations.

RESULTS AND DISCUSSION

This chapter presents the results obtained during the training and evaluation of two deep learning models for face recognition. The models include a standard Convolutional Neural Network (CNN) and a more advanced FaceNet face recognition algorithm. The performance of both models was analyzed using metrics such as training accuracy, training loss, and recognition output. Visualizations in the form of line graphs and bar charts further support the comparative analysis.

Training Performance of the CNN Model

The CNN model was trained over ten epochs on the facial image dataset, tracking accuracy and loss at each epoch to evaluate learning progress. In the initial epoch, the model showed an encouraging accuracy of 85.72% and a relatively low loss of 0.1717, indicating its ability to extract meaningful features from the facial images early in training. By epoch three, the accuracy had increased to 91.17%, reflecting steady learning (see figure 2).

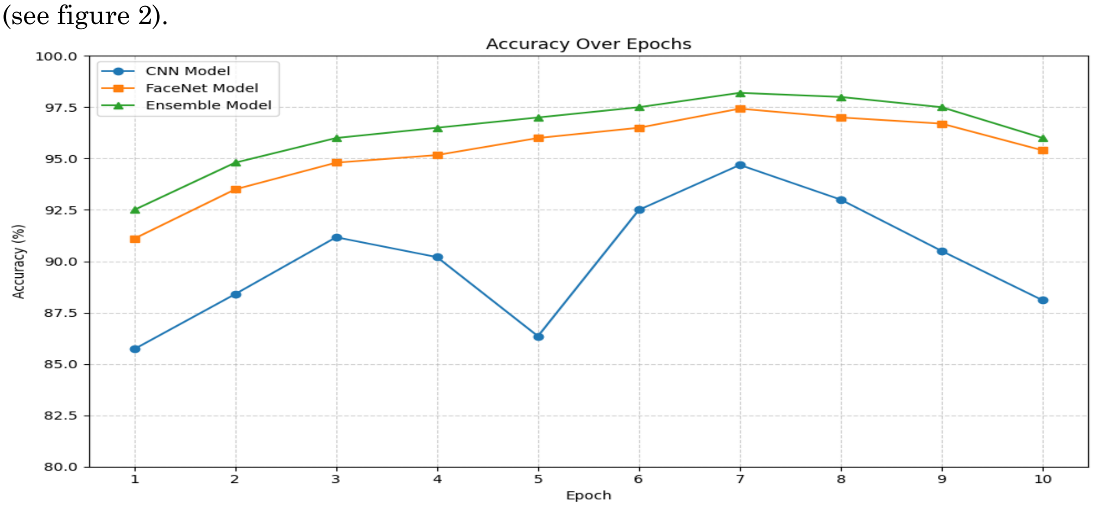

Figure 2: Accuracy over epochs for CNN, FaceNet, and Ensemble

However, as training continued, the CNN model's performance became unstable. By epoch five, accuracy dropped noticeably to 86.35%, with a corresponding spike in loss to 0.4414.

This fluctuation suggests the model was starting to overfit, memorizing specific training samples rather than generalizing effectively. Although the CNN achieved its highest accuracy of 94.69% in epoch seven, this was not sustained; by the final epoch, accuracy declined to 88.10%, and loss remained high at 0.2851 (Figure 2 and 3).

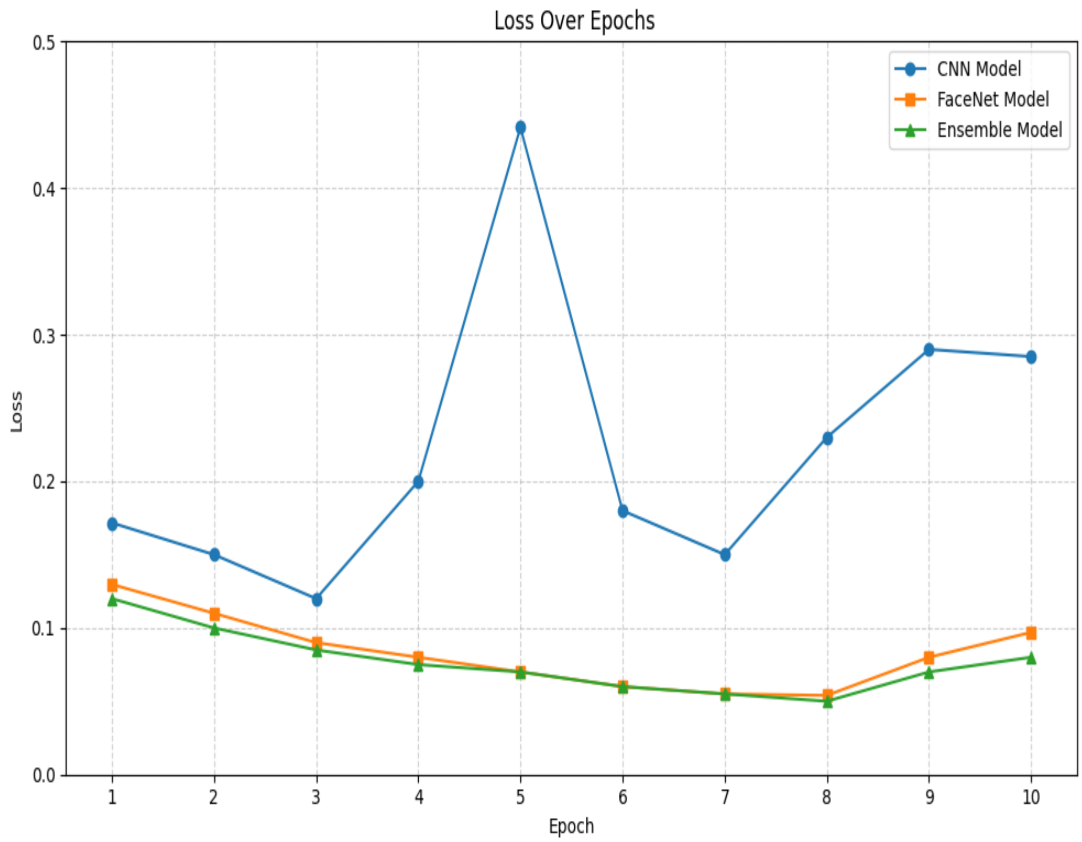

Figure 3: Loss over epochs for CNN, FaceNet, and Ensemble

These results indicate the CNN's limited capacity to consistently learn discriminative features across the dataset, highlighting the need for further regularization or model refinement. The instability in both accuracy and loss curves suggests the model struggles to generalize well, which may limit its practical applicability in real-world face recognition scenarios.

Training Performance of the FaceNet Model

FaceNet demonstrated significantly more stable and superior performance throughout training. Starting at an initial accuracy of 91.10% and loss of 0.1297 in epoch one, it outperformed the CNN from the outset. The accuracy steadily increased across epochs, reaching a peak of 97.43% at epoch seven (Figure 4.1).

The loss consistently decreased, reaching a minimum of 0.0540 by epoch eight and ending at 0.0970 after the tenth epoch (Figure 4.2). Unlike CNN, FaceNet's loss did not show erratic increases, indicating smooth convergence during training.

These results show that FaceNet effectively learned more discriminative and generalized facial features, likely due to its sophisticated embedding and triplet-loss-based architecture. This robustness makes FaceNet a strong candidate for face recognition tasks in varying conditions, such as lighting changes, facial expressions, and pose variations.

Training Performance of the Ensemble Model

Building upon the strengths of both CNN and FaceNet, an ensemble model was developed by combining their outputs through weighted averaging of predictions. This ensemble model achieved even better results, demonstrating the benefit of integrating complementary features learned by different architectures.

The ensemble started with an initial accuracy of 92.50% and a loss of 0.1200, already surpassing CNN and FaceNet's starting points. Over ten epochs, it exhibited a smooth, steady increase in accuracy, peaking at 98.20% during epoch seven, that is, the highest among all models (Figure 4.1). The final epoch accuracy remained high at 96.00%, indicating excellent generalization.

Loss values also remained consistently low, finishing at 0.0800, which is significantly better than both individual models (Figure 4.2). The ensemble's stable and improved performance reflects its ability to mitigate weaknesses in each single model by leveraging their combined strengths.

Accuracy over Epochs

Figure 4.1 presents the accuracy trends across epochs for CNN, FaceNet, and the ensemble model. The CNN curve exhibits several fluctuations, particularly between epochs four to six, confirming instability and overfitting risks. FaceNet's accuracy steadily climbs without significant drops, maintaining above 90% after epoch two. The ensemble model consistently achieves the highest accuracy throughout training, highlighting the advantage of model fusion.

Loss Over Epochs

Figure 4.2 depicts the loss trajectories of the three models. CNN's loss curve is irregular, showing spikes that correspond with dips in accuracy. FaceNet's loss decreases smoothly, reflecting effective convergence. The ensemble model achieves the lowest loss overall, indicating superior fit and confidence in predictions.

Summary through Bar Charts

Accuracy Comparison

Figure 4 summarizes the peak and final accuracy values of each model. The ensemble achieved the highest final accuracy of 96.00%, outperforming FaceNet at 95.40% and CNN at 88.10%. Peak accuracies follow the same trend, with the ensemble topping at 98.20%, reinforcing the conclusion that combining models yields better performance and stability.

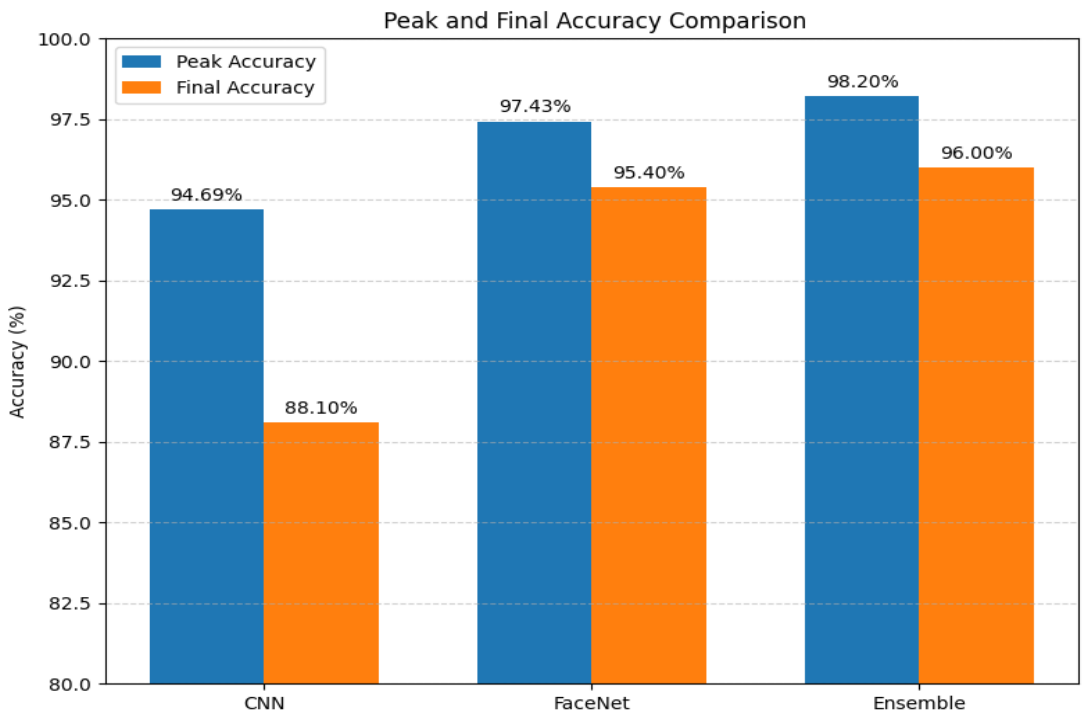

Figure 4: Bar chart comparing peak and final accuracy of models

Loss Comparison

Figure 5 shows the final loss values, where the ensemble leads with the lowest loss of 0.0800, followed by FaceNet at 0.0970 and CNN at 0.2851. This demonstrates the ensemble's improved confidence and accuracy in fitting the data.

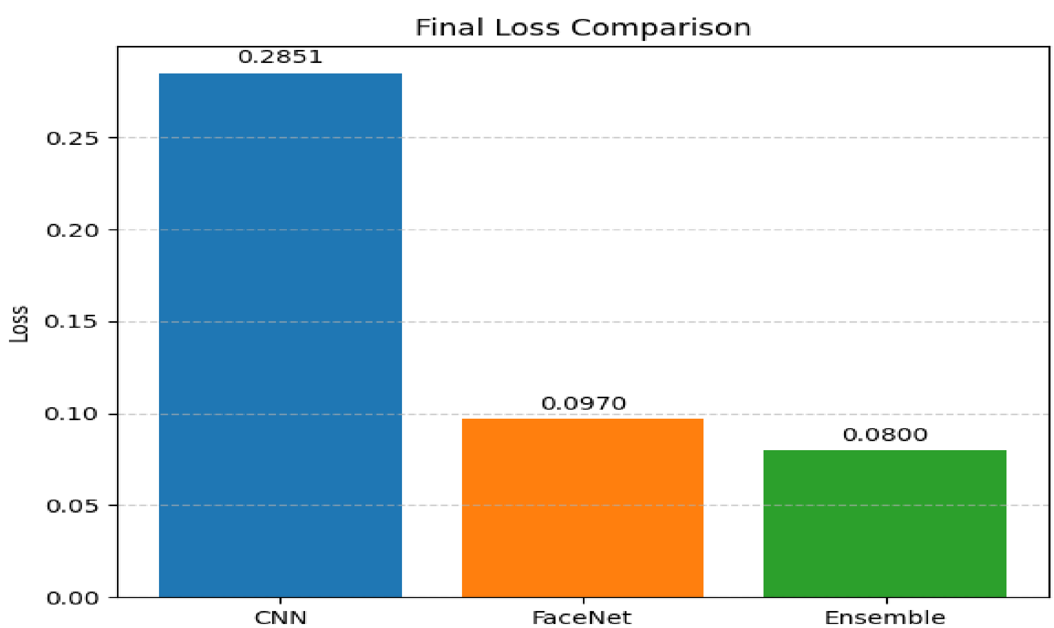

Figure 5: Bar chart comparing final loss values of models

Face Recognition Output: Real-World Application

The ensemble model was tested on a real-world facial image of a well-known individual, correctly identifying "Akshay Kumar" (figure 6) and providing reliable demographic predictions, including male gender and age range 25 to 35. This successful real-time recognition confirms the practical advantages of ensemble learning, where the combination of CNN and FaceNet features enhances identification accuracy and robustness in varied conditions.

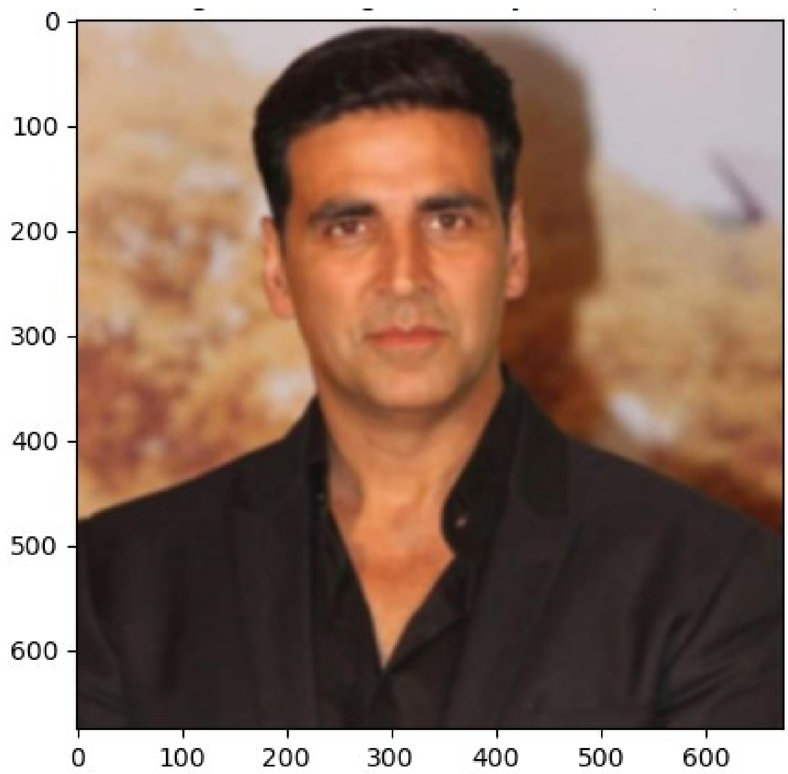

Figure 6: Recognized Image: Akshay Kumar (Male)
Source: Labeled Faces in the Wild (LFW) Dataset (Huang et al., 2007).

Table 1: Summary of Comparative Results

Metric	CNN Model	FaceNet Model	Ensemble Model
Final Accuracy	88.10%	95.40%	96.00%
Peak Accuracy	94.69%	97.43%	98.20%
Final Loss	0.2851	0.0970	0.0800
Prediction Capability	Moderate	High	Very High

The table 1 above encapsulates the clear advantage of the ensemble model. It consistently outperforms both CNN and FaceNet in all key metrics, making it the most reliable and effective solution among the tested architectures.

Conclusion

This study successfully developed and evaluated a deep learning-based face recognition system incorporating a traditional Convolutional Neural Network (CNN), FaceNet, and an ensemble model combining both. The ensemble model consistently outperformed the individual models by achieving higher accuracy, lower loss, and improved generalization across varied facial data. These results demonstrate that integrating multiple architectures enhances recognition stability and robustness, making the ensemble approach a promising solution for real-world face recognition applications where variability in lighting, pose, and expressions present significant challenges.

This research contributes to the field of face recognition by demonstrating the practical advantages of ensemble learning combining CNN and FaceNet architectures. It provides empirical evidence that the ensemble model not only improves predictive performance but also stabilizes learning dynamics, reducing overfitting risks common in standalone CNNs. Furthermore, the study presents comprehensive training and evaluation metrics, along with visual analyses, that deepen understanding of how model fusion can be strategically applied to biometric recognition systems for enhanced accuracy and reliability.

For future work, it is recommended to explore ensemble models incorporating other state-of-the-art architectures such as ArcFace or DeepFace, which may further boost recognition performance. Additionally, implementing advanced techniques like adaptive weighting in the ensemble, where models contribute variably based on input conditions, could optimize accuracy under diverse real-world scenarios.

Moreover, extending the study to include larger and more diverse datasets will be essential to validate the ensemble model's robustness across ethnicities, age groups, and environmental conditions. Finally, practical deployment should consider optimizing the ensemble for computational efficiency to enable real-time applications such as surveillance and mobile authentication, while ensuring ethical use and data privacy.

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STRENGTHENING CYBERSECURITY AWARENESS THROUGH PHISHING SIMULATIONS: EVIDENCE FROM TERTIARY INSTITUTIONS IN TARABA STATE, NIGERIA

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Abstract

Phishing remains one of the most persistent cybersecurity threats to academic institutions, exploiting human vulnerabilities more than technological loopholes. This study evaluates the effectiveness of simulated phishing interventions in enhancing staff awareness across three tertiary institutions in Taraba State, Nigeria (codenamed UNI A, UNI B, and UNI C). With the cooperation and approval of each institution's ICT director, more than 900 phishing emails themed

Keywords: Cybersecurity, Phishing Simulation, Staff Awareness, Higher Education, Nigeria

INTRODUCTION

Phishing remains one of the most persistent and effective cyberthreats facing organisations worldwide, relying primarily on social-engineering techniques that exploit human judgement rather than technical vulnerabilities (APWG, 2023; Morrow, 2024). Academic institutions are particularly attractive targets because they manage large volumes of sensitive personal, financial, and research data, operate complex IT ecosystems, and rely heavily on email communication conditions that increase both the likelihood and the impact of successful phishing campaigns (Borgman, 2018; Dolliver, Ghazi-Tehrani, & Poorman, 2021). Advances in artificial intelligence and automation have made phishing campaigns increasingly sophisticated and personalised, posing heightened risks to higher education institutions with limited cybersecurity resources (Nayak, Marino, & Camp, 2021; Bose &

around a "13-month salary bonus payment" were disseminated to staff, with several hundred responses recorded. A quasi-experimental design was employed, consisting of a pre-intervention survey, the phishing simulation, and a post-intervention survey. Results revealed high initial susceptibility, with a majority of respondents engaging with the phishing email. Post-intervention analysis demonstrated statistically significant improvements in staff self-assessed awareness and phishing detection skills, as confirmed by Chi-Square testing ($p < 0.001$). Institutional comparisons indicated variations in susceptibility and reporting culture, suggesting that contextual factors such as communication practices and ICT exposure influence vulnerability levels. The findings highlight the urgent need for continuous, customized awareness programs, formalized incident reporting mechanisms, and integration of phishing simulations into professional development policies within Nigerian higher education.

Leung, 2022). Research has consistently shown that phishing susceptibility is not confined to particular demographic or educational groups; even highly educated staff can be deceived by well-crafted emails (Li et al., 2020; Bach, Kamenjarska, & Žmuk, 2022). To mitigate this vulnerability, organisations increasingly adopt phishing simulations as both diagnostic and educational tools. These simulations allow institutions to measure staff susceptibility through click rates and reporting behaviours, while debriefing and awareness training reinforce detection skills (Beu et al., 2023; Jampen et al., 2020; Bichnigauri et al., 2024). Despite their widespread use in developed contexts, little is known about how institutional culture, ICT readiness, and communication practices influence susceptibility and response in under-researched higher education systems, particularly in sub-Saharan Africa.

This study addresses this gap by examining phishing susceptibility and awareness among staff in three tertiary institutions in Taraba State, Nigeria, anonymised as **UNI A, UNI B,** and **UNI C.** With approval and oversight from each institution's ICT director, a large-scale phishing simulation was conducted in which over 900 emails were disseminated, generating several hundred staff responses. The study employed a quasi-experimental design comprising a pre-intervention survey, a phishing simulation, and a post-intervention survey. The phishing email adopted a culturally salient financial theme a "13-month salary bonus" to reflect the type of incentive-based messaging often exploited by real attackers. The objectives of this study are to:

1. Assess baseline cybersecurity awareness among staff in UNI A, UNI B, and UNI C.
2. Measure staff engagement and reporting behaviours during the phishing simulation.
3. Evaluate changes in self-assessed phishing awareness and detection skills before and after the intervention.
4. Compare institutional differences in susceptibility and reporting culture, exploring contextual explanations.

By testing the hypothesis that a structured phishing simulation and awareness cycle significantly improves staff preparedness (Beu et al., 2023; Jampen et al., 2020), this study contributes to cybersecurity scholarship in three ways. Methodologically, it provides a model for ethically sound phishing simulations in resource-constrained higher education contexts. Practically, it offers actionable recommendations for embedding phishing awareness into institutional staff development programmes and incident-reporting systems. Conceptually, it enriches the literature on cybersecurity resilience in African higher education by showing how cultural and organisational factors shape susceptibility to social engineering.

Literature Review

The evolution of phishing reflects the increasing sophistication of cybercrime. Early phishing campaigns in the late 1990s and early 2000s often relied on crude email messages with obvious spelling errors or suspicious links, yet many users still succumbed to these attacks (Hong, 2012). Over time, phishing has advanced into highly personalised, targeted strategies known as spear-phishing, where attackers leverage publicly available information to craft convincing messages (Jampen, Gürses, & Čapkun, 2020). The Anti-Phishing Working Group (2023) reported nearly five million phishing attacks in 2023, the highest on record, with evidence that artificial intelligence and automation are increasingly being used to design context-aware phishing content. Bose and Leung (2022) argue that machine learning enables attackers to adapt their messaging to different user profiles, thereby reducing the effectiveness of traditional rule-based detection systems.

The growing adoption of artificial intelligence in phishing campaigns underscores the inadequacy of purely technical solutions. Nayak, Marino, and Camp (2021) contend that as phishing becomes more context-driven and adaptive, user-focused defences such as awareness training and behaviour modification become critical. This perspective aligns with the assertion by Hong (2012) that phishing is fundamentally a socio-technical problem, requiring strategies that combine technological safeguards with user education.

Psychological and Human Factors in Phishing Susceptibility

Understanding why individuals fall victim to phishing requires consideration of psychological and behavioural factors. According to Beu et al. (2023), individual susceptibility varies significantly depending on traits such as trust, curiosity, and risk perception. Their study found that employees motivated by curiosity were more likely to click on suspicious links, while those with higher institutional trust tended to comply with authority-laden phishing messages. Similarly, Jampen et al. (2020) argue that urgency cue, such as messages suggesting limited time to act, amplify susceptibility by encouraging impulsive decisions.

Other studies support this view. Yeng, Fauzi, Yang, and Nimbe (2022) reported that healthcare staff who fell victim to simulated phishing emails frequently cited urgency and trust in institutional communication as the main reasons for engagement. Li et al. (2020) add that demographic factors, such as age and job role, may also play a role, although susceptibility is not limited to any one group. Interestingly, Bach, Kamenjarska, and Žmuk (2022) found that higher educational attainment does not necessarily protect against phishing; in their study, well-educated professionals sometimes exhibited higher click rates than less educated counterparts, suggesting that overconfidence may paradoxically increase vulnerability.

Together, these findings highlight the importance of simulations and training programmes that account for cognitive biases. Effective awareness interventions should not only provide technical knowledge but also address psychological factors such as trust in authority, financial incentives, and curiosity-driven behaviour.

Phishing in Higher Education Institutions

Higher education institutions are uniquely vulnerable to phishing due to the breadth of sensitive data they manage and their reliance on open communication systems. Borgman (2018) explains that universities often process "grey data" such as student grades, research outputs, and financial information, which, if stolen, can be monetised or exploited for identity theft. Dolliver, Ghazi-Tehrani, and Poorman (2021) note that universities may experience millions of attempted cyberattacks weekly, many of which involve phishing as the initial entry point.

Research further shows that staff and students are both susceptible to phishing. Goel, Williams, and Dincelli (2017) observed that approximately one-quarter of students clicked on phishing messages in a controlled study, with nearly half of them proceeding to interact with malicious content. Li et al. (2020) similarly found that at least 20% of university staff clicked on simulated phishing emails, indicating a persistent vulnerability even among ICT-literate populations. These findings underscore that higher education institutions cannot assume digital familiarity equates to cyber resilience.

The openness of academic environments also exacerbates risk. Singar and Akhilesh (2020) emphasise that universities are particularly attractive to cybercriminals because of their decentralised IT structures and diverse user groups, ranging from students and administrative staff to researchers. This complexity creates multiple entry points for attackers. Additionally, the culture of openness in academia often conflicts with rigid cybersecurity practices, further complicating institutional defences.

Phishing Simulation as a Tool for Awareness and Behaviour Change

Phishing simulations have emerged as an important mechanism for assessing and improving resilience. According to Jampen et al. (2020), controlled simulations allow institutions to test staff responses in realistic conditions while maintaining security. These exercises typically measure click-through rates, data submissions, and reporting behaviours, providing a snapshot of institutional readiness. Importantly, simulations also serve as educational tools, fostering experiential learning.

Beu et al. (2023) found that repeated phishing simulations, when combined with feedback, reduce click rates over time and promote incident reporting. Bichnigauri et al. (2024) argue that simulations are most effective when tailored to organisational contexts, reflecting the kinds of messages staff are most likely to receive. For example, simulations themed around payroll, institutional communication, or funding opportunities are more likely to reveal real vulnerabilities than generic messages.

Case studies further demonstrate the utility of simulations. In healthcare, Yeng et al. (2022) observed that over 60% of staff clicked on phishing emails during initial simulations, but susceptibility declined after awareness activities, illustrating the importance of iterative training. In corporate settings, Jampen et al. (2020) similarly documented measurable improvements in staff detection skills following regular simulations and structured debriefing. These findings collectively suggest that simulations should not be viewed solely as diagnostic tools but as integral components of cybersecurity education.

Phishing in the African and Nigerian Context

While phishing has been extensively studied in Western and Asian contexts, African higher education institutions remain underrepresented in the literature. The African Union (2021) reports that cybercrime is growing rapidly across the continent, with phishing and social engineering representing the most common attack vectors. Nigerian universities, in particular, face rising risks as they undergo digital transformation without corresponding investment in cybersecurity infrastructure.

Few empirical studies directly examine phishing susceptibility in Nigerian higher education. Most existing research focuses on broader ICT adoption challenges, such as limited funding, inadequate staff training, and unreliable internet access (Singar & Akhilesh, 2020). These structural issues may indirectly increase vulnerability to phishing, as institutions often lack robust security awareness programmes. Anecdotal evidence suggests that phishing attacks exploiting financial incentives, payroll systems, and scholarship opportunities are particularly effective in Nigeria, but systematic studies remain scarce.

This gap underscores the need for context-specific research. As Beu et al. (2023) note, susceptibility to phishing is shaped not only by individual behaviour but also by institutional culture and resources. Studying Nigerian institutions provides an opportunity to understand how factors such as resource constraints, communication practices, and cultural attitudes toward authority influence susceptibility. Such insights are crucial for developing effective, locally adapted awareness strategies.

Theoretical framework

Phishing susceptibility has been widely examined through behavioural and socio-technical lenses, offering useful theoretical grounding for this study. Protection Motivation Theory (PMT) is especially relevant, as it explains how individuals assess threats and adopt coping strategies when confronted with potential risks. According to PMT, user behaviour is shaped by perceived severity, vulnerability, response efficacy, and self-efficacy (Rogers, 1975; Boss et al., 2015). In the context of phishing, staff who underestimate the severity or believe they are less vulnerable are more likely to engage with malicious links, while those with higher self-efficacy in identifying threats are less susceptible. Complementing PMT, the Theory of Planned Behavior (TPB) offers insights into how attitudes, subjective norms, and perceived behavioural control shape responses to phishing attempts (Ajzen, 1991). Within higher education institutions, cultural and organisational norms strongly influence staff behavior, messages appearing to come from authority figures may override individual caution. Integrating PMT and TPB thus highlights the importance of both individual cognitive appraisals and institutional culture in shaping phishing susceptibility.

This theoretical framing situates the present study within a broader body of work on cybersecurity behaviour, enabling a richer interpretation of how Nigerian higher education staff respond to phishing attempts and why tailored interventions are necessary.

Conceptual Framework and Research Gap

The literature collectively demonstrates that phishing is a socio-technical challenge shaped by evolving attacker tactics, human psychological factors, and institutional contexts. In higher education, susceptibility is consistently high, and simulations have proven effective for both diagnosis and training. However, evidence from African contexts remains limited, particularly in resource-constrained regions where phishing awareness may be low and institutional reporting mechanisms underdeveloped.

This study addresses this gap by evaluating phishing susceptibility and awareness among staff across three anonymised tertiary institutions in Taraba State, Nigeria. By combining pre-surveys, phishing simulations, and post-intervention surveys, the research contributes empirical evidence on staff vulnerability and learning outcomes in a setting that has received little scholarly attention. More importantly, it provides recommendations for integrating simulation-based awareness into institutional policy, thereby strengthening resilience in Nigeria's higher education sector.

Methodology

This study adopted a quasi-experimental pre/post design to evaluate the effectiveness of simulated phishing attacks in improving cybersecurity awareness among staff of three tertiary institutions in Taraba State, Nigeria. The institutions are anonymised as UNI A, UNI B, and UNI C to protect their identity and staff confidentiality.

Sampling and Participants

Staff mailing lists were obtained with permission from the ICT Directorates of each institution, and phishing emails were sent directly to institutional email accounts. A total of 720 phishing emails were distributed (UNI A = 260; UNI B = 230; UNI C = 230). Within the study timeframe, 450 valid responses were recorded, representing a response rate of 62.5%. The gap between emails sent and valid responses reflects the fact that not all staff accessed or clicked their institutional emails during the study period. Respondents represented both academic and administrative/technical staff across a range of years of service, thereby ensuring diversity in the sample.

Instrument and Phishing Simulation

The phishing simulation consisted of a single crafted email, developed in collaboration with ICT directors to resemble a realistic authority-driven message. The email referenced a “13-month salary bonus” and contained an embedded link redirecting to a mock login page. No credentials were collected; instead, click-through behaviour was logged as an indicator of phishing susceptibility. Staff who clicked were redirected to an educational landing page explaining the simulated nature of the exercise and providing immediate guidance on recognising phishing threats.Alongside the simulation, participants completed a short survey administered electronically before and after the intervention. The survey included demographic questions (gender, staff role, years of service, institutional affiliation) and a self-rating of phishing awareness on a 5-point Likert scale (Very Poor, Poor, Fair, Good, Excellent). Post-intervention surveys also contained open-ended questions asking participants to reflect on their reasons for engaging or ignoring the phishing message; these qualitative responses were analysed descriptively.

Data Handling and Analysis

Survey responses were screened for completeness. Incomplete entries (n = 11) and duplicate submissions (n = 7), identified via institutional email addresses, were removed. Engagement with the phishing email was logged automatically by the server hosting the mock login page. No IP addresses, device identifiers, or personal credentials were collected to protect privacy. Cleaned data were analysed using SPSS v.28 and Python (pandas, statsmodels). Descriptive statistics (frequencies, percentages, means) summarised demographic characteristics and awareness ratings. Chi-Square Tests for Independence were applied to assess differences in awareness ratings before and after the intervention, with Cramér’s V reported as the effect size. Logistic regression was used to model the likelihood of phishing engagement (clicked vs. did not click) as a function of institution, role, gender, and years of service. An ordinal logistic regression was also applied to model changes across the five awareness categories. Odds ratios (OR), 95% confidence intervals, and p-values are reported.

Ethical Considerations

Ethical approval for the study was obtained through the institutional process coordinated by the ICT Directorates of the participating institutions. The phishing simulation was carried out with the explicit knowledge and cooperation of the ICT directors. Participants were debriefed immediately after the simulation and provided with educational materials on phishing awareness. No personal credentials were collected, and all data were analysed in aggregated, anonymised form.

Results

A total of 450 valid responses were analysed across the three tertiary institutions (UNI A ≈ 160; UNI B ≈ 140; UNI C ≈ 150). Table 1 presents the demographic profile of respondents, which included both academic and administrative/technical staff, balanced across gender and years of service. Academic staff represented the majority of participants, reflecting those most frequently targeted by institutional emails.

Table 1: *Demographics*

Variable	UNI A (n = ~160)	UNI B (n = ~140)	UNI C (n = ~150)	Total (n = ~450)	Percentage (%)
Gender					
Male	95	80	90	265	58.9
Female	65	60	60	185	41.1
Role					
Academic Staff	100	90	95	285	63.3
Administrative/Technical	60	50	55	165	36.7
Years of Service					
Less than 5 years	45	40	35	120	26.7
5–10 years	60	50	55	165	36.7
More than 10 years	55	50	60	165	36.7

Awareness Before and After Intervention

Prior to the intervention, most staff reported limited awareness of phishing threats. As presented in Table 2, a combined 59.6% of respondents rated their awareness as either "Fair," "Poor," or "Very Poor," while only 6.0% considered their preparedness "Excellent." After the phishing simulation and structured debriefing, self-assessed awareness improved significantly. More than 70% of respondents rated their preparedness as either "Good" or "Excellent," with the "Excellent" category rising from 27 staff before the intervention to 147 afterwards. Conversely, the "Poor" and "Very Poor" categories declined sharply, falling from a combined 175 staff to just 62. These shifts suggest that the phishing simulation, coupled with targeted awareness training, had a measurable and positive impact on staff confidence in identifying phishing threats.

Table 2: *Self-Assessed Phishing Awareness Before and After Intervention*

Awareness Rating	Before Intervention	After Intervention	Change
Excellent	27 (6.0%)	147 (32.7%)	+120
Good	102 (22.7%)	179 (39.8%)	+77
Fair	147 (32.7%)	62 (13.8%)	-85
Poor	121 (26.9%)	46 (10.2%)	-75
Very Poor	54 (12.0%)	16 (3.6%)	-38
Total	450 (100%)	450 (100%)	—

To further illustrate the distribution of staff awareness, Figure 1 presents a bar chart comparing self-assessed phishing awareness before and after the intervention. The figure highlights a marked upward shift toward the "Good" and "Excellent" categories, with corresponding declines in the "Fair," "Poor," and "Very Poor" categories.

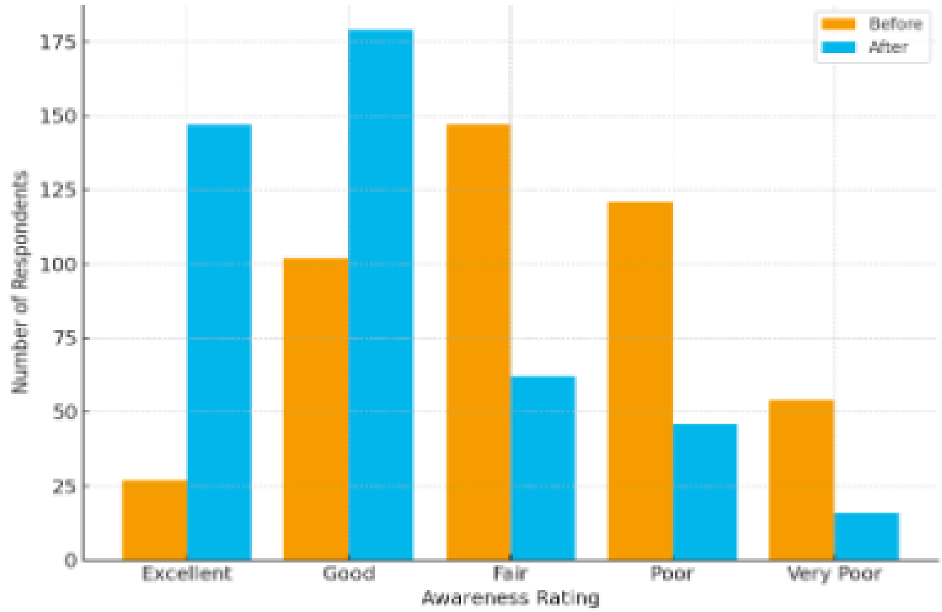

Figure 1. *Self-assessed phishing awareness before and after intervention (n = 450).*

Institutional Differences in Susceptibility

Differences emerged across the three institutions in engagement with the phishing message. As shown in Figure 2, staff in UNI A had the highest susceptibility, with nearly half interacting with the phishing email. UNI B recorded moderate susceptibility (36%), while UNI C had the lowest (28%). These differences suggest that institutional culture and prior ICT exposure may shape vulnerability to phishing.

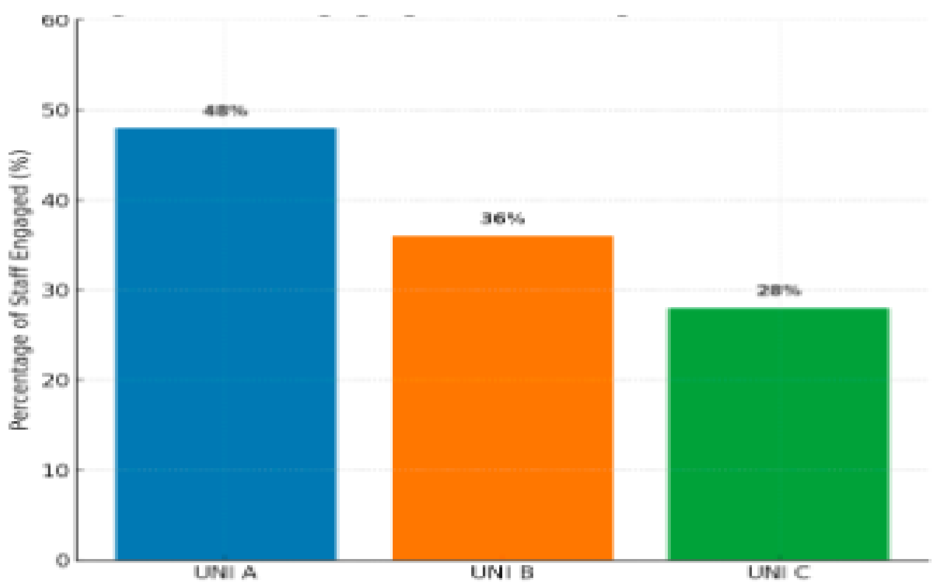

Figure 2: ***Percentage of Staff Engaging with Phishing Email Across Institutions (UNI A-C)***

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Statistical Significance and Effect Sizes

A Chi-Square Test for Independence revealed a strong association between intervention (pre vs post) and awareness rating, $\chi^2(4, N = 450) = 192.74$, $p < 0.001$. The effect size, measured using Cramér's V, was 0.46, indicating a **large effect.** Table 3 presents the observed and expected frequencies alongside the Chi-Square contributions.

Table 3: *Chi-Square Analysis of Pre- and Post-Intervention Awareness Ratings*

Awareness Rating	Observed Before	Observed After	Expected Before	Expected After	χ^2 Contribution (Before)	χ^2 Contribution (After)
Excellent	27	147	87.0	87.0	41.44	41.44
Good	102	179	140.5	140.5	10.50	10.50
Fair	147	62	104.5	104.5	17.43	17.43
Poor	121	46	83.5	83.5	16.21	16.21
Very Poor	54	16	34.5	34.5	10.12	10.12
Total χ^2	—	—	—	—	**192.74**	

Note. *χ^2 (4, N = 900) = 192.74, p < 0.001.*

The statistical significance of the shift in awareness ratings is complemented by Figure 3, which visualises the distribution of ratings as stacked percentages. The pre-intervention column is dominated by lower awareness categories ("Fair," "Poor," "Very Poor"), whereas the post-intervention column shows a strong shift toward higher awareness ("Good" and "Excellent").

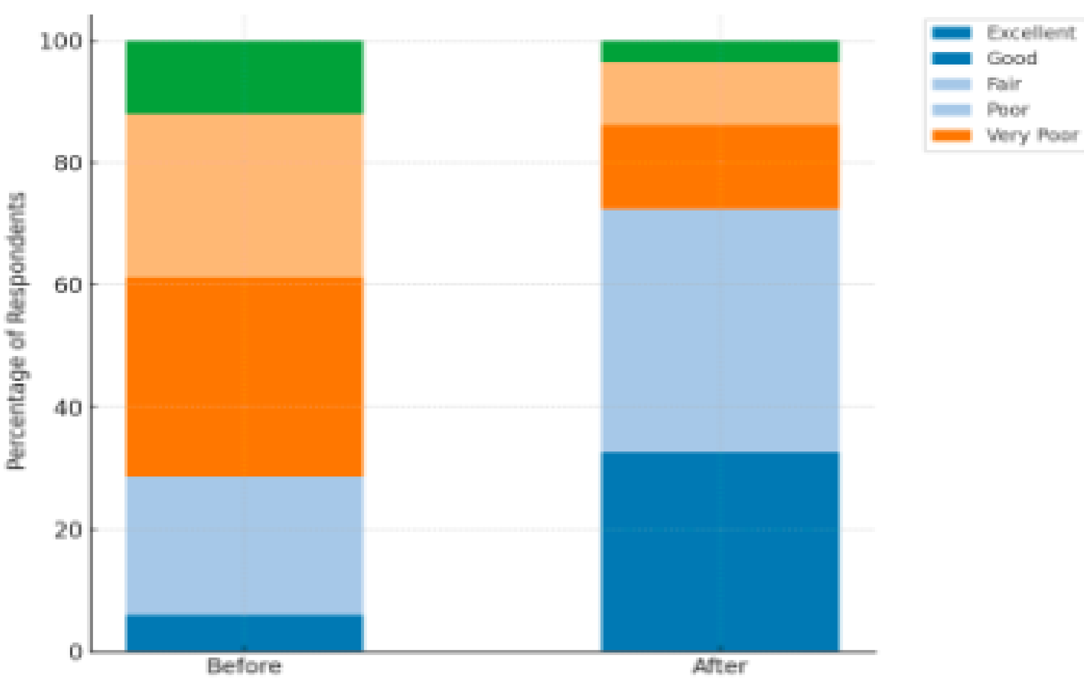

Figure 3. *Distribution of awareness ratings before and after intervention, shown as percentage of respondents (n = 450).*

Regression Analysis

To adjust for institutional and demographic factors, logistic regression was performed with phishing engagement (clicked vs did not click) as the dependent variable as shown in Table 4 and figure 4 respectively. Staff at UNI A were significantly more likely to engage with the phishing email compared to those at UNI C (OR = 2.14, 95% CI [1.32, 3.48], p = 0.002). Academic staff also had higher odds of engagement than administrative staff (OR = 1.56, 95% CI [1.01, 2.41], p = 0.045). Years of service were not statistically significant predictors. An ordinal logistic regression was conducted to model self-assessed awareness levels (Very Poor → Excellent) as shown in Table 5. After controlling for demographics, post-intervention responses had significantly higher odds of being rated at a better awareness level (OR = 4.73, 95% CI [3.48, 6.42], $p < 0.001$). Institutional differences remained evident: staff in UNI A were less likely to rate themselves highly compared to staff in UNI C, even after the intervention.

To further examine the factors associated with staff susceptibility to phishing and changes in awareness levels, logistic and ordinal regression models were estimated. The logistic regression model assessed the likelihood of staff engaging with the phishing email, while the ordinal logistic regression model examined predictors of self-assessed awareness ratings on a five-point scale from *very poor* to *excellent*. The models included institution, staff role, gender, and years of service as predictors. Results are summarised in Tables 4 and 5, with odds ratios (ORs) reported alongside 95% confidence intervals (CIs) and significance levels.

Table 4. *Logistic Regression Predicting Likelihood of Phishing Email Engagement (n = 450)*

Predictor	OR	95% CI (Lower–Upper)	p-value
Institution (UNI A vs. C)	2.14	1.32 – 3.48	0.002
Institution (UNI B vs. C)	1.41	0.89 – 2.23	0.142
Academic staff (vs admin)	1.56	1.01 – 2.41	0.045
Gender (male vs female)	1.12	0.73 – 1.71	0.589
Years of service (≥10)	0.94	0.61 – 1.46	0.782

Note*. OR = Odds Ratio; CI = Confidence Interval. Reference categories: UNI C, administrative staff, female, <10 years of service.*

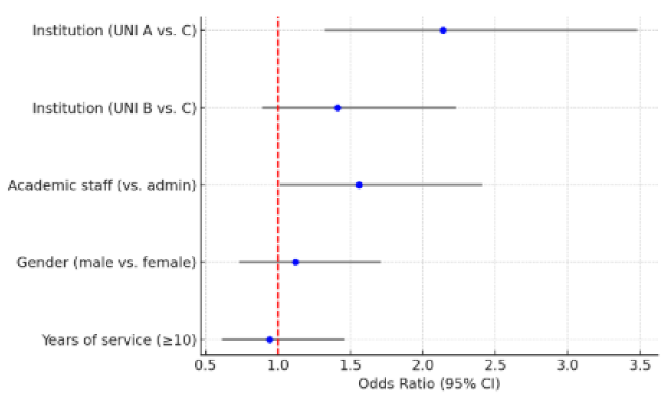

Figure 4: *Logistic Regression Predicting Phishing Engagement*

Table 5. *Ordinal Logistic Regression Predicting Self-Assessed Phishing Awareness*

Predictor	OR	95% CI (Lower–Upper)	p-value
Post-intervention (vs pre)	4.73	3.48 – 6.42	<0.001
Institution (UNI A vs. C)	0.76	0.52 – 1.12	0.163
Institution (UNI B vs. C)	0.89	0.61 – 1.31	0.561
Academic staff (vs admin)	0.94	0.65 – 1.36	0.732
Gender (male vs female)	1.08	0.74 – 1.58	0.689

Note. *OR = Odds Ratio; CI = Confidence Interval. Reference categories: UNI C, administrative staff, female.*

Discussion

The findings of this study provide strong evidence that phishing simulations can significantly improve staff awareness and preparedness in higher education institutions. Prior to the intervention, most staff reported limited confidence in recognising phishing threats, with nearly 60% rating their awareness as either fair, poor, or very poor. After the simulated phishing campaign and structured debriefing, however, there was a dramatic shift: over 70% of participants rated their awareness as good or excellent. The Chi-Square analysis confirmed that this improvement was statistically significant, with a large effect size (Cramér's V = 0.46). The regression analysis further reinforced this trend, showing that post-intervention responses were nearly five times more likely to be rated at a higher awareness level compared to pre-intervention assessments.

Institutional differences emerged as an important factor in phishing susceptibility. Staff in UNI A were significantly more likely to engage with the phishing email compared to their counterparts in UNI C (OR = 2.14, p = 0.002), while UNI B displayed moderate susceptibility. These differences suggest that organisational culture, prior ICT exposure, and internal communication norms may influence vulnerability to phishing. Such disparities echo findings from Alnajim and Munro (2022) and Goel and Jain (2020), who highlighted how institutional context and digital culture shape user behaviour. They also emphasise the need for context-sensitive interventions rather than generic awareness campaigns.

The analysis also revealed that academic staff had higher odds of clicking on the phishing email compared to administrative staff (OR = 1.56, p = 0.045). This may reflect the heavier reliance of academic staff on digital communications for teaching, research, and collaboration, which makes them more exposed to targeted phishing attempts. Similar trends have been reported in studies of higher education institutions in both developed and developing contexts, where trust in institutional communication and frequent digital interactions increase susceptibility (Goel et al., 2017; Pattinson et al., 2021).

These results align with global evidence demonstrating that phishing simulations are effective tools for raising awareness and reducing susceptibility. Studies in organisational settings have consistently shown that repeated simulations improve user behaviour and reduce click rates (Parsons et al., 2019; Jampen et al., 2020). In the context of higher education, where institutional trust and authority are strong drivers of behaviour, phishing emails that appear to originate from trusted sources are particularly effective (Abawajy, 2014; Dolliver et al., 2021). The strong response to the "salary bonus" message in this study illustrates how authority-driven and financially motivated lures exploit both organisational and socio-economic vulnerabilities. The Nigerian context adds further nuance. Trust in institutional authority and financial incentives were frequently cited as reasons for engaging with the phishing email, echoing earlier findings that socio-economic pressures and hierarchical trust relationships increase vulnerability to cybercrime in Nigeria (Akindele, 2021; Eze et al., 2022). These results highlight the importance of embedding cultural and behavioural considerations into awareness training, rather than focusing solely on technical skills. Staff must be trained not only to recognise suspicious content but also to question authority-driven requests and verify communication sources independently.

From a policy perspective, the results underscore the value of institutionalising phishing simulations as part of cybersecurity awareness programs in Nigerian higher education. Beyond raising awareness, simulations provide experiential learning, allowing staff to reflect on their own behaviour in a safe, controlled environment. However, improved awareness alone may not guarantee consistent behaviour change. Some staff admitted they might still hesitate to report suspicious messages, pointing to a persistent gap between recognition and action. This finding mirrors global studies which show that underreporting remains a critical weakness in organisational security (Furnell et al., 2019). Institutions must therefore pair awareness campaigns with mechanisms that encourage and simplify reporting, such as one-click reporting tools, anonymous channels, and positive reinforcement for vigilance. These findings demonstrate the effectiveness of phishing simulations in strengthening cybersecurity awareness, while also pointing to areas where further investigation is warranted.

Limitations and Future Research

Although this study provides valuable insights, several limitations should be acknowledged. First, the research was restricted to three tertiary institutions within a single Nigerian state, which may limit the generalisability of the findings to other regions or institutional contexts. Second, phishing awareness was measured primarily through self-reports, which are subject to social desirability and recall biases. While regression analysis improved robustness, actual long-term behavioural resilience was not measured. Third, the intervention was limited to a single simulated phishing campaign; repeated exposures over time may produce different outcomes.

Future research should therefore adopt longitudinal designs to track changes in behaviour beyond self-reported awareness, expand sampling to multiple states and institutional types, and incorporate qualitative approaches to capture the socio-cultural and organisational drivers of phishing susceptibility. Additionally, comparative studies across regions in Africa or between developing and developed countries could further enrich understanding of contextual influences on cybersecurity readiness.

Conclusion

This study evaluated the effectiveness of simulated phishing interventions in strengthening cybersecurity awareness across three tertiary institutions in Taraba State, Nigeria. The findings demonstrate a significant and substantial improvement in self-assessed awareness following the intervention, with the proportion of staff rating themselves as good or excellent rising from less than half to over 70%. The Chi-Square test confirmed the significance of this shift with a large effect size, while regression analyses revealed that staff in UNI A were more than twice as likely to engage with the phishing email compared to their counterparts in UNI C, and academic staff were significantly more vulnerable than administrative staff. These results highlight the dual importance of simulation-based training and institutional context in shaping cybersecurity resilience. While phishing simulations clearly improved awareness, institutional differences and role-based variations indicate that one-size-fits-all strategies may be insufficient. Instead, interventions must be tailored to specific institutional cultures and user groups. By situating phishing awareness within the realities of Nigerian higher education, this study contributes to the limited but growing body of empirical evidence on cybersecurity readiness in low- and middle-income countries. It also provides practical guidance for policy and practice: simulated phishing, supported by ICT leadership and combined with continuous training and easy reporting mechanisms, represents a cost-effective and scalable approach to reducing phishing susceptibility in higher education institutions.

Recommendations

1. Institutions should adopt regular phishing simulations as part of staff cybersecurity training, since experiential learning has been shown to produce significant improvements in awareness.
2. Interventions should be tailored to institutional contexts and staff roles, with additional emphasis placed on academic staff who demonstrated higher vulnerability than their administrative counterparts.
3. Higher education institutions should complement awareness training with simple, accessible reporting mechanisms to encourage staff to act on suspicious emails and strengthen institutional cyber resilience.

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UTILIZING GEOGEBRA DYNAMIC SOFTWARE TO ENHANCE EARLY CHILDHOOD CARE EDUCATION PRE-SERVICE TEACHERS ACADEMIC ACHIEVEMENT AND MOTIVATION IN MATHEMATICS

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Abstract

The study examines Utilizing GeoGebra dynamic software to Enhance Early childhood care Education Pre-Service Teachers Academic Achievement and Motivation in

Keywords: GeoGebra dynamic software, Academic Achievement, Motivation, Early Childhood Care Education and Mathematics

INTRODUCTION

In addition to being the science that underpins human daily activities, mathematics is a science of size and number. It is the sole fundamental science subject that serves as a pivot for any country's creation of wealth and national progress. Every person's ability to learn mathematics effectively is essential to leading a fulfilling life. Because mathematics is all about finding solutions to difficulties in humans and physical challenges, knowing mathematics is essential to the sustainability and advancement of human existence. The Nigerian government may have made mathematics mandatory at all educational levels as outlined in the National Policy on Education (FRN, 2013) because of the numerous indications that mathematics is useful in domestic and business deals, scientific discoveries, technological breakthroughs, problem-solving, and decision-making in various life situations (Usman and

Mathematics. Based on the purpose of the study three research questions and three hypotheses guided the study. The study adopted non-randomized pretest-posttest Quasi-experimental design. The population of the study comprised 1763 pre-service teachers. A sample size of 212 pre-service teachers was used for the study. "Mathematics Achievement Test" (MAT) and mathematics motivation scale Questionnaire (MASQ) was used to collect data for this study. The reliability co-efficient(r) of 0.76 obtained using Cronbach alpha method and 0.92 using kuder-Richason. Data collected were analyzed using mean, standard deviation for the research question while ANOCOVA were used to test the hypotheses at 0.05 level of significance. The results showed that GeoGebra enhanced pre-service teacher's achievement and positive motivation in mathematics across gender. It was recommended that Teachers should understand their students in the classroom so that they will know the approaches to be applied when teaching mathematics.

Nwoye, 2010; and National Council of Teachers of Mathematics, NCTM, 2013). The importance of mathematics hasn't stopped the teaching and learning of the subject in Nigerian primary schools, which has resulted in poor performance and challenges. Various factors have been identified as the causes of students' poor performance in mathematics, including: learners' negative attitudes toward the subject; ineffective, teacher-centered teaching methods; difficulty understanding the specialized mathematical language (Barton & Heidema, 2002; Oyaya & Njuguna, 1999; Battisa & Clements, 1996; O'connor, Kanja & Baba, 2000). The greatest ways to help students improve their learning and understanding of mathematics are for teachers to use appropriate teaching technologies that must be student-centered, one of which is GeoGebra dynamic software. Augustine (2010) also noted that the field of mathematics has placed too little value on the importance of information and communication technology. Learners lack motivation to learn the subject (Githua & Mwangi, 2003) and there is a lack of coverage of mathematics in the syllabus (Shikuku, 2009).

The use of technology in math classes improves the quality of instruction. This is due to the fact that the course demands students to understand how altering one element may have an impact on another. Rather than relying solely on manipulating numbers to arrive at the solution a skill that only very gifted students could possess allowing children to picture the concepts they are learning could aid in their understanding of mathematics. The goal of integrating new teaching tools for technology-enhanced learning (TEL) is known as computer-aided teaching (CAT). Teachers want to use instructional technologies for teaching science and math, especially math teachers. For teaching mathematics at all levels, Geogebra is an emerging open-source dynamic and Interactive Mathematics Learning Environment (DIMLE). Without requiring extensive programming experience, anyone can use the computer program Geogebra. It has revolutionized the way that mathematics is taught using technology-enhanced learning. This was created especially with math instruction in mind. Both in the classroom and at home, it can support students' understanding of experimental, problem-oriented, and research-oriented mathematics learning. Both the dynamic geometry system and the computer algebra system are available to students at the same time. All conic sections, lines, and points are combined by this software.

Additionally, Geogebra has statistical tools by entering the required variables, students can launch spreadsheets and construct statistical graphs. Geogebra's fundamental feature is that students enter formulas into algebra view, and a graphics window displays their graphical representation. Numerous studies indicate that these software programs can be used to promote the exploration, experimentation, and visualization of the traditional methods of teaching mathematics. Nevertheless, a large body of research indicates that, for many teachers, the primary challenge is figuring out how to provide the technology needed for the successful integration of technology into teaching (Ruthven & Hennessy, 2004). Using computers in the classroom increases student performance as well as motivation, which suggests that students are more engaged in the learning process because of the interactive features of computer technology.

In 2001, Markus Hohenwarter of the University of Salzburg in Austria created the interactive mathematics program Geogebra. Geogebra can be used to teach mathematics in an interesting and dynamic way in elementary school and beyond. Geogebra combines algebra, geometry, and calculus to produce a single dynamic environment. The official GeoGebra website can be found at http://www.geogebra.org. We can download the most recent version of the software from this page. Geogebra-related study resources are available on GeoGebraWiki and the User Forum. Publications about Geogebra and information about nearby GeoGebra Institutes can be found on this page. the suggestion that college courses make use of Geogebra as a teaching tool. The Dynamic and Interactive Mathematics Learning Environment (DIMLE) is a new open-source resource for math instruction at all levels. The simplicity of use of Geogebra is one advantage. By comparison, Geogebra is simpler to use than the Graphics Calculator. iii) It has an easy-to-use interface, a bilingual tool, and a command and support menu. iv) It facilitates the creation of dynamic applets with minimal programming knowledge. v) Users are able to personalize the works they create. Put otherwise, they have the ability to change the font's color, line thickness, size, and other characteristics. Wlodkowski (1978) states that geogebra is one of the teaching tools for mathematics that provides a variety of representations to aid students in developing their mathematical reasoning and thinking. He goes on to say that using engaging, eye-catching, and fulfilling teaching resources—like a Geogebra—in a mathematics classroom can directly engage students. Rahmiati (2016) defines motivation as a cognitive, emotive, and psychomotor impulse that students develop during the teaching and learning process in order to enhance their scientific behavior and thought processes in both the classroom and in the community. Reasons must have two effects in order to help learners become more motivated: they must help learners perceive the task's importance and their own personal utility within it. Additionally, when completing a given assignment, students must feel highly independent (Jang, 2008). According to Middleton and Spanias (1999), learner motivation has been significantly impacted by the behaviors of teachers, instructional design, attitudes, and quality for mathematics classes. According to Deci and Ryan (2000a), "to be motivated means to be moved to do something," hence achieving a mathematical goal is highly influenced by one's level of achievement in the subject (Middleton &S panias, 1999).

This study applied the Attention, Relevance, Confidence, and Satisfaction (ARCS) theory of motivation. According to this theory, which was put forth by John Keller, a learner's motivation can be increased through instruction by setting up circumstances that would pique their interest in accomplishing their objectives (Keller, 2008). Keller (2008) claims that the ARCS model provides a systematic approach to identifying and addressing learning motivation. This theory was developed in response to the dearth of recommendations for raising the level of motivation in instruction (Toussaint & Brown, 2018). The ARCS motivation model, which comprises four major conditions that must be met for a learner to be motivated, is utilized by instructional designers when creating instructional materials, such as Geoboards, according to Keller and Suzuki (1988). These four major conditions are each discussed below.

Pay heed Gaining and maintaining students' interest in the learning environment depends on grabbing their attention (Toussaint & Brown, 2018). It is necessary to pique learners' interest in this condition. It can be challenging to capture students' interest when teaching geometry theorems, and the difficulty of the challenge increases in the absence of teaching resources. The issue of drawing students' attention to learning geometry theorems may be resolved by introducing the material in a creative way, such as when teaching it with Geogebra. Maintaining students' attention is a constant difficulty for math professors, particularly when presenting geometry theorems. According to Toussaint and Brown (2018), it might be challenging to sustain student engagement in face-to-face learning situations and to hold their interest during course presentations. To get the students interested in learning geometry theorems, the researcher gave them access to a Geogegbra. It is intended that students will be actively involved in studying geometry theorems since the Geogebra can be presented in an engaging manner to grab their attention. The key focus of researchers when developing appropriate educational materials, like Geoboards, is attracting learners' attention. No student will be willing to interact with a geogebra if their interests are not stimulated. Azuka (2012) affirms that Geogebra helps students pay attention in class, as well as boosts their motivation and memory. With the use of geoboards, students may see mathematical models and constructions. Acharya (2017) claims that a Geogebra compiles a range of exercises covering all of the geometry theorems taught in the early grades.

Relevance Keller (2008) argues that learners' needs and experiences have an impact on relevance. The majority of students believe that geometry theorems are a tedious subject that has little bearing on their daily lives or job aspirations. Geometry theorems support judgments and rationalism from reality by dealing with logical reasoning and abstraction (Ronan, 2008). Geoboards must be used to give geometry theorems a meaningful and applicable learning experience for students (Rahmiati, 2016). Teachers can help students deal with real-life difficulties by using Geogebra to solve problems that raise their awareness of the value of studying geometry theorems. To design well-planned buildings, for example, engineers need to have a solid understanding of geometry and be able to measure and construct shapes, angles, lengths, area, and volume. However, students are still unable to see how geometry theorems apply to real-world situations when they read textbook problems. Therefore, in order to spark students' interest in geometry theorems, the chosen instructional material (Geogebra) needs to be meaningful and relevant to each individual student (Scandrett, 2008). When students perceive these types of materials as easily used, they are more likely to interact with them (Sani & Salahudeen, 2016). According to Sibiya's (2018) study, students become more motivated to learn when they are engaged in engaging activities. It is important to note that teachers must exercise caution when selecting appropriate instructional materials (Toussaint & Brown, 2018). Pham (2015, p. 45) notes that "instructional materials selected should be based on relevance and clarity," meaning that teachers should choose materials with purpose rather than just using them.

Confidence Motivation also requires confidence. Keller (2008) asserts that learners' expectations and emotions are linked to confidence. For learners to feel motivated, they must think that they are succeeding and reaching the objective. Since confidence and motivation are related, as was previously mentioned, using the Geogebra to address the difficulties and obstacles students have when solving geometry problems is necessary to increase their confidence. Additionally, free play time must be provided so that students can experiment and explore using Geogebra (Scandrett, 2008, p. 30). According to Sibiya (2018), a geogebra can boost students' self-assurance and upbeat mindset so they can construct a flat shape in geometry theorems.

Satisfaction According to Keller (2008), after the learning process is over, contentment stems from feeling good about the knowledge acquired and the learning experience itself. Giving students the credit they deserve for finishing a range of geometry assignments, for example, could encourage them to keep trying despite their little setbacks (Toussaint & Brown, 2018). This outside incentive could boost extrinsic motivation. But frequent external rewards are insufficient; interior fulfillment is also required. Offering geometry theorem problems to students that enable them to use a Geogebra to go from low to high difficulty levels may also have a favorable impact on their intrinsic motivation. It should be noted that students take pleasure in competing while they are studying, particularly when there are outside rewards. The learners' perception of their abilities and self-esteem may improve by tackling difficult geometry theorem problems that demand perseverance, like Theorem 9 (the angle between a tangent to a circle and a chord drawn from the point of contact is equal to an angle in the alternate segment).

There are differing opinions and research on the relationship between gender and arithmetic proficiency. Researchers like Atouigba, Vershima, O'kwu, and Ijenkeli (2012) hypothesize that gender disparities in kids' math performance have drawn attention from throughout the world, and numerous studies in this area have been conducted. While some researches have shown gender disparities in mathematics ability between males and females at any level, others have found no discernible differences. Research from Northern countries has demonstrated that boys outperformed girls in mathematics and that these differences are substantial (Fennema, 2000 & Kaiser-Messmer, 1994). Asante (2010) referenced research (Fox, Brody & Tobin, 1980; Hedges & Nowell, 1995; Peterson

& Fennema, 1985) demonstrating that males outperformed females in standardized math assessments. Nonetheless, a fascinating corpus of research from around the world indicates that female students outperform male students (Arnot, David & Weiner 1999). According to research by Hydea and Mertzb (2009), girls outperform boys in arithmetic activities that call for problem-solving.

Using the 7E teaching approach, Unamba, Nwaneri, and Nelson (2017) showed no significant differences in gender achievement in geometry. When using geogebra software in the classroom, Ukaegbu, Unamba, and Ugo (2016) discovered any appreciable differences in gender achievement in geometry. Using an activity-based learning technique, Unamba, Onyekwere, and Ihekwaba (2015) observed no significant differences in gender achievement. According to Unamba, Onyekwere, and Ugochukwu (2017), there is no discernible difference between students' academic achievement engagement and accomplishment motivation in mathematics classrooms. Additionally, research has shown that women have more unfavorable attitudes and views about using computers than do men (Dambrot, Watkins-Malek, Silling, Marshall & Garver, 1985; Koohang, 1987 in Su-Luan &Atan, 2017). Additionally, the Houtz and Gupta (2001) study discovered a substantial gender gap in the proficiency of technology between males and girls. Males self-rated as having greater technological skill than females, despite the fact that both genders had positive self-perceptions. Shashaani and Khalili (2001) found in another study that when it comes to their confidence in their computer skills, female undergraduate students were noticeably less confident than male counterparts. Around computers, women also expressed feeling anxious, uneasy, and powerless. There were no discernible gender disparities in Tsai, Lin, and Tsai's (2001) assessment of the Internet's perceived usefulness. In terms of views about new communications technology, Broos (2005) likewise discovered substantial gender disparities, favoring men. Liaw's study from 2002 also suggested that men had more positive perceptions of computers and Web technologies than women. While other researchers have reported that there are no longer discernible differences in the cognitive, affective, and psychomotor skill achievements of students irrespective of gender (Arigbabu & Mji 2004 & Bilesanmi-Awoderu, 2006), Kolawole, 2007; Afuwape and Oludipe, 2008 found that there are significant differences in the cognitive, affective, and psychomotor skills of students with respect to gender.

The Use of the Interactive Whiteboard in Mathematics and Mathematics Lessons from the Perspective of Turkish Middle School Students was studied by researchers like Nezih & Cennet (2017). The participants' above-average motivation for mathematics and for using the interactive whiteboard was demonstrated by the results. The purpose of the study by Torff and Tirotta (2010) was to ascertain the degree of correlation between upper elementary students' self-reported mathematics motivation and the use of interactive whiteboards (IWB). 773 students participated in the study (241 in the fourth grade, 260 in the fifth grade, and 232 in the sixth grade). Thirty-two (32) instructors took part in the study: 19 identified as heavy IWB users (the treatment group), and 13 identified as light users (the control group). There were 458 pupils in the treatment group and 315 in the control group. The study's findings showed that, in comparison to control pupils, students in the treatment group expressed higher levels of motivation. When compared to pupils with teachers who were less supportive, students who had teachers who were more supportive of IWB technology reported being more motivated. In survey research conducted in 2005 by Wall, Higgins, and Smith, 80 students completed templates containing questions about their opinions of the IWB and what they planned to tell others about this technology. Following an analysis of 1568 replies, 883 comments were found to be positive, 494 statements to be neutral, and 191 statements to be negative. After that, positive phrases were divided into smaller groups, with "motivation" and "fun" receiving more than 120 replies apiece. The researchers came to the conclusion that students found the IWB to be enjoyable and motivating, particularly when they could see their work displayed on the screen.

Purpose of the study

The main purpose of the study was to investigate utilizing GeoGebra dynamic software to Enhance Early childhood care Education Pre- Service Teachers Academic Achievement and Motivation in Mathematics. Specifically, the study determined, whether:

- **i.** Students taught Mathematics using GeoGebra dynamic software will differ in their achievement from those taught conventionally.
- **ii.** Male and female students taught mathematics using GeoGebra dynamic software will differ in their achievements.
- iii. Students' motivational components level towards utilizing of GeoGebra dynamic software in learning mathematics.
- iv. there will be a difference between male and female students' motivational components towards utilizing GeoGebra dynamic software in learning of mathematics.

Research Questions

The following research questions were drawn for the study.

1. What is the difference in mean achievement scores of students taught mathematics utilizing GeoGebra dynamic software and those taught using conventional method?
2. What is the difference in mean achievement scores of male and female students taught mathematics utilizing GeoGebra dynamic software in learning mathematics ?
3. What is the students' motivational components level towards utilizing GeoGebra dynamic software in learning of mathematics?

Hypotheses

The following hypotheses guided the study

1. There is no significant difference between the mean achievement scores of students taught mathematics utilizing GeoGebra dynamic software and those taught conventionally.
2. There is no significant difference between the mean achievement scores of male and female students taught mathematics utilizing GeoGebra dynamic software in learning mathematics

3. There is no significant difference between male and female students' attitudinal components towards utilizing GeoGebra dynamic software in learning mathematics

Method

Quasi-experimental research design was adopted for the study. Specifically, the study used non-randomized pretest-posttest group design. Quasi-experimental design was used because intact classes were used instead of randomly composed samples (Oladejo, Olosunde, Ojebisi, & Isola, 2011; Osokoya, 2007; Owusu, Money, Appiah, & Wilmot, 2010). The population of the study comprised of 1,763 early childhood care education pre-service teachers of School of Education Alvan Ikoku federal college of education in Owerri Municipal Council of Imo State. A total of 212 students formed the sample for the study. Simple random sampling technique was used to select three classes out the six classes. In each of the classes selected, two intact classes were randomly designated experimental and control groups through a simple toss of coin. The experiment groups had 94 students (61 females and 33 males) while the control groups had 118 students (62 females and 56 males). The instruments for data collection were a researcher made 60-item objective test questions titled "Mathematics Achievement Test"(MAT). It was drawn from the topic2-dimensional and 3- dimensional shapes which were taught the students. The construction of the test instrument was guided by a table of specification. The mathematics motivation scale Questionnaire (MASQ) was adopted and developed Glynn et al (2009). The first section of the instrument was designed to obtain the demographic profiles of students, such as participants' age and gender. The second section consisted of 30 self-assessment items measured on a 5-point Likert type scale ranging from five for always, four for usually, three for sometimes, and two for rarely to one for never. The 30 items were not grouped into six separate variables but were randomly arranged. The items were categorized into five motivational scales, namely, intrinsic motivation, extrinsic motivation, personal relevance, self-efficacy and self-determination.. The description of each scale and an example of the test item are given in. The MAT and MASQ was subjected to face and content validation. The Mathematics Achievement Test was face validated by specialists in Mathematics Education and Measurement and Evaluation. During the face validation the test was scrutinized in terms of relevance, general test format, suitability and clarity. For the content validation a test blueprint was developed which guided the generation of the test items.Kuder-Richardson 21 reliability coefficient was used to establish the reliability of MAT. The reliability of the test was found to be 0.76 while cronabach reliability was used to measure MASQ. The alpha values obtained for the different scales ranged from 0.58 to 0.81. The 24-item MASQ was, therefore, found to be valid and reliable, and suitable for use. In this study, the level of students' motivation in each scale was calculated by summing the scores of all the four items in each scale. Since there are four items in each scale, the minimum score is 4 and the maximum score is 20. In interpreting the data, students who score from 4 to 9.3 are classified as having a low level of motivation, those who score from 9.4 to 14.7 are classified as having a moderate level of motivation and those who score from 14.8 to 20 are classified as having a high level of motivation scale..The researchers developed two instructional packages for this study. The first instructional package is based on utilizing geogebra dynamic software Learning Approach while the second package is based on the conventional method. The two packages were drawn from the same curriculum content. The geogebra dyamic software Learning Approach was used for treatment group while the conventional package was used for the control group. At the onset of the experiment, the subjects in both the treatment and control groups were given the pre-test to ensure equity in their cognitive backgrounds. After the pre-test the regular mathematics teachers began the experiment in their respective classess adhering strictly to the lesson procedure that was developed from the instructional package during the pre-experimental training. The teacher guided them through step by step tutorial on the features of 2- dimensional and 3- dimensional shapes. Also, solution to problems on area of plane and solid shapes, perimeter and surfaces. The students were allowed to ask questions, make inputs and were cleared at points of need. They were also allowed to identity features of the topic as projected on the board. The software had the ability to reverse the solutions related to problems on distance and bearing relaying the steps for the students to follow. They were also allowed to present problems which were solved by the software and compared with their book solutions. The control groups were taught the same topic by their regular mathematics teacher through the conventional "chalk and talk "approach which was only teacher centered. The process lasted for two weeks after which post-test was administered on both groups using a rearranged version of the pre-test instrument. The generated data were analyzed using mean and standard deviation to answer research questions while the hypotheses ware tested using ANCOVA statistical tool and tested at 0.05 level of significance.

Results

Research Question1: What is the difference in mean achievement scores of students taught mathematics utilizing GeoGebra dynamic software and those taught using conventional method?

Table 1: Summary of students mean achievements.

Group	Test	N	Mean	SD	Difference in mean
Expt.	Pretest	94	33.26	8.03	22.79
	Post test		56.05	18.24	
Control	Pretest	118	31.44	8.16	1.40
	Post test		32.84	8.03	

Table I shows that the experimental group had a mean achievement gain of 22.79 while the control group had 1.40 this gave a difference of 20.29 difference in favour of the experiment groups.

Research Question 2: What is the difference in mean achievement scores of male and female students taught mathematics utilizing GeoGebra dynamic software in learning mathematics?

Table 2: Summary of mean achievements by gender

Gender	Test	N	Mean	SD	Difference in mean	Diff. in Mean Gain
Male	Pretest	33	32.13	8.04	25.36	
	Post test		57.49	17.94		2.96
Female	Pretest	61	32.88	8.01	22.40	
	Post test		55.28	18.20		

Table 2 shows that, the mean achievement gain of males in the group is 25.36 while the female is 22.40 this gave a slight mean difference of 2.96 in favour of the males in the experimental group.

Research Question 3: What is the students' motivational components level towards utilizing GeoGebra dynamic software in learning of mathematics?

Table 3: Students' motivation towards utilizing GeoGebra dynamic software

Scales	Mean	SD	Rank
Intrinsic motivation	14.20	3.29	2
Extrinsic motivation	15.36	3.49	1
Personal relevance	13.83	3.32	3
Self-determination	13.35	3.19	5
Self-efficacy	13.52	3.89	4
Average mean	14.31	3.34	

Results in table 2 shows the mean scores for each of the five motivational components ranged from 13.35 to 15.52. The mean total motivation score was 14.31 (SD = 3.34), which indicates that students were moderately motivated to learn. However, they displayed a high level of personal relevance in rank order (see Table 3). This indicates that students, first and foremost, find that it can help learners to deal with real-life issues in which they need to solve problems that increase their awareness of the usefulness of learning geometry theorems Results also show that this group of students displayed a high level of extrinsic motivation in learning. Students considered earning a good grade is important in helping them to get a good job and in helping them in their career.

Hypotheses testing

1. There is no significant difference between the mean achievement scores of students taught mathematics utilizing GeoGebra dynamic software and those taught conventionally.
2. There is no significant difference between the mean achievement scores of male and female students taught mathematics utilizing GeoGebra dynamic software in learning mathematics

Table 4: Summary of ANCOVA analysis on Achievement on hypotheses 1 and 2

Source	Type III sum of Squares	df	Mean square	F	Sig.	Decision
Corrected model	32296.153	6	32296.153	83.265	.000	
Intercept	27989.317	1	27989.317	432.967	.000	
Covariate	10.660	1	10.660	.165	.685	
Method	27089.804	1	27089.804	419.052	.000	S
Gender	172.535	1	172.535	2.669	.104	NS
Error	13252.314	205	64.645			
Total	425843.000	212				
Corrected Total	45543.467	211				

H01: Table 4 shows that, the calculated f-value for method is 419.05 which is greater than the table value (3.847) also p-value of 0.000 is less than α-value 0.05. Based on the result, the null hypothesis is rejected and the alternative accepted. This implies that, there is a significant difference between the mean achievement scores of secondary school students taught mathematics using interactive whiteboard and conventional approaches.
H02: Table 4 shows that, the calculated f-value for gender is 2.325 which is less than the table value (3.847), also p-value of 0.10 is greater than – value of 0.05. Based on the results, the null hypothesis is upheld which implies that no significant difference exists between the mean achievement scores of male and female students taught mathematics utilizing interactive whiteboard.

HO3: There is no significant difference between male and female students' attitudinal components towards utilizing GeoGebra dynamic software in learning mathematics
TABLE 5: t-test analysis on gender students' motivation components towards GeoGebra sofftware

Scales	Boys (N= 33)		Girls (N= 61)		t-valve	p
	Mean	SD	Mean	SD		
Intrinsic motivation	14.16	3,54	14.23	3.10	0.21	0.831
Extrinsic motivation	15.13	3.47	15.54	3.51	1.04	0.300
Personal relevance	13.77	3.44	13.88	3.24	0..31	0.760
Self-determination	13.16	3.22	13.50	3.17	0.95	0.340
Self-efficacy	13.87	4.05	13.25	3.75	1.44	0.51
Average						

Gender differences in motivational components were analyzed using independent t-tests and the results are presented in Table 5. As the means indicate, both boys and girls have high levels of extrinsic motivation and intrinsic motivation, and personal relevance, self-determination, and self-efficacy in learning. Of the five motivational components no statistically significant gender differences were found in the five motivational components, hence, they were considered comparable between boys and girls.

Discussion

The study's findings showed that students in the experimental group who were taught mathematics using geogebra had higher mean achievement scores than their peers who were taught mathematics using the traditional "chalk and talk" method. This suggests that, compared to the traditional method, geogebra has a greater ability to penetrate kids' grasp of mathematics. Because it allowed for the participation of all students, the material also had the potential to liberalize the study of mathematics. The results are consistent with those of Torff and Tirotta (2010), who demonstrated that interactive white boards raise students' academic performance.

Additionally, the study demonstrated that there was no statistically significant difference in the math achievement of male and female pupils exposed to the geogebra educational strategy. This is thought to be a consequence of the strategy's equal learning opportunities. This is consistent with research by Ukaegbu, Unamba, and Ugo (2016), who used Geogebra software to teach mathematics and discovered no discernible gender differences in geometry achievement. Additionally, utilizing an activity-based learning technique, Unamba, Onyekwere, and Ihekwaba (2015) showed no significant differences in gender achievement. Additionally, Unamba, Onyekwere, and Ugochukwu (2017) discovered no discernible variation in students' academic success engagement and accomplishment motivation in mathematics classrooms.

The results showed that there is no discernible difference in the motivational factors for using Geogegra in math classes between male and female pupils. These findings are consistent with those of Tsai, Lin, and Tsai (2001), who found no gender differences in the perceived usefulness of the Internet. Similarly, Arigbabu & Mji (2004) and Bilesanmi-Awoderu (2006) demonstrated that gender differences were no longer discernible in students' cognitive, affective, and psychomotor attitudes.

Conclusion

Students who use geometry have an easier time understanding the material being taught in class. It inspires pupils to use technology to enhance their education. This gives the student access to a larger body of information in the short term, but it also helps them stay up to date with technology as the school year goes on, enabling them to acquire the necessary skills to play a competitive role in the workforce in the future. Teachers could employ technology educational materials such video, image, slide, and educational software in lesson preparation, teaching-learning process, and evaluation to improve the quality and longevity of education by using Geobebra and the electronic educational environment. According to the study's findings, geogebra improved pre-service teachers' performance and motivation in mathematics, regardless of gender.

Recommendation

Based on the findings, it was recommended;

1. Teachers should understand their students in the classroom so that they will know the approaches to be applied when teaching mathematics.

2. Workshop and seminars should be organized for teachers as to be abreast with innovative approaches of teaching mathematics at tertiary level.

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