Digital Innovations & Contemporary Research in SCIENCE, ENGINEERING & TECHNOLOGY
Vol. 12. No. 1, 2024 Series

Article Citation Format
Oweimieotu, Amanda Enaodona, Akazue, Maureen Ifeanyi, Edje, Abel Efetobore & Asuai Clive (2024): Designing a Hybrid Genetic Algorithm Trained Feedforward Neural Network for Mental Health Disorder Detection. Journal of Digital Innovations & Contemporary Research in Science, Engineering & Technology.
Vol. 12, No. 1. Pp 49-62.
dx.doi.org/10.22624/AIMS/DIGITAL/V11N4P4
www.isteams.net/digitaljournal.

Article Progress Time Stamps

Article Type: Research Article
Manuscript Received 17th January, 2024
Review Type: Blind Peer
Final Acceptance: 9th March, 2024

Designing a Hybrid Genetic Algorithm Trained Feedforward Neural Network for Mental Health Disorder Detection

Oweimieotu, Amanda Enaodona[1*], Akazue, Maureen Ifeanyi[2], Edje, Abel Efetobore[3] & Asuai Clive[4]
[1,2,3,4] Department of Computer Science, Delta State University Abraka, Nigeria;
E-mail: amandaoweimieotu@gmail.com; akazue@delsu.edu.ng, edjeabel@delsu.edu.ng; asuaiclive007@gmail.com
*Corresponding Author: Amanda Enaodona Oweimieotu

ABSTRACT

This research delves into the innovative application of feed-forward neural networks (FNNs) specifically the multi-layer perceptron (MLP). MLP is a flexible algorithm due to its ability to adapt to different real-world problems amongst other features, and this makes it a preferred machine learning algorithm in the early detection of mental health disorders. MLP's number of layers and the number of neurons per layer changes to accommodate these abilities. MLP was chosen for this work because they can model non-linear relationships found in a dataset as well as the fact that the algorithm is efficient in accuracy detection which is lacking in other types of FNN. This study focused on developing and optimizing MLP architectures to achieve heightened accuracy in identifying mental health disorders. Original dataset that was used comprise 334 rows (datapoints) and 31 columns (features) and Only 27 features were quantifiable. We utilized the first 13 features in the dataset for this research work as too many features will affect the training time. The model performance was evaluated using Accuracy, Precision, F1 Score, Recall, and the results of the model evaluation showed that early detection of mental health disorders is predictable using this type of Feed-forward Neural network, with an Accuracy of 96%, Recall of 80%, F1 Score of 77%, Sensitivity 90%, and Specificity of 88% when compared to previous research with lower accuracy of 81.75% amongst the other result they got for the other parameters. Furthermore, by using widely collected datasets and employing advanced machine learning techniques such as feature importance technique for optimization of the initial result got, this approach contributes significantly to the field of early detection of mental health disorders.

Keywords: Mental Health Disorder, Feedforward Neural Network, Machine Learning, Early Detection, Artificial Intelligence

1. INTRODUCTION

Mental health disorder is a condition that is known to affect one's responses to happenings around them and the generality of a person's being [1]. Research have shown that since the COVID-19 pandemic, mental health illnesses have exponentially increased due to underlying diseases and ailments with its victims.

Digital technology is seen to play a significant and novel role in making help available throughout the day, all week long [2]. [3] also found out from their research that mental health disorder is a growing concern in today's society with an increasing number of cases recorded since 2019.

Mental health disorders are one of the many worries of this century in healthcare and this arises from the fact that lots of person's which includes both adults, adolescents, and children can be sufferers and will not even be aware that they have this disease [4]. It affects the entirety of a person's reasoning, feelings, and behavior which hampers how children can learn and the overall functionality of adults within society [5], and this makes early detection paramount [6]. Some kinds of mental health disorders are depression, post-traumatic stress disorder (PTSD), bipolar disorder, and schizophrenia amongst others [4]. Stress, anxiety, and other variables are predictors that someone would likely suffer from mental health disorder [7].

The World Health Organization (WHO) defines Mental Health as the state for which each individual according to their capabilities – can handle the stress level brought on to them by life's daily experiences [8], and still be able to function effectively as required of them as they contribute to the general wellbeing of the society [9]. To properly identify and treat patients' illnesses, their health conditions need to be known [10]. Over the years, prediction models have been applied to solve human problems [11]–[13]. The importance of early detection thus, is both necessary and critical as undetected mental health conditions can quickly escalate into debilitating challenges, which can harm the individuals concerned, the families, and society [14].

With the ever-growing knowledge and impact of early detection to mental health disorders, an increased demand for advanced cum efficient methods that can detect and intervene is required. The potential benefits of a machine learning-driven early detection system are multifaceted [15]. Not only does it promise swifter identification of the 'at-risk' and 'borderline' individuals; It also allows for a more distinct understanding of the diverse manifestations of mental health conditions. Moreover, the scalability of machine learning systems could bridge the gap in mental health resources, especially in regions where access to traditional healthcare is limited.

The emergence of machine learning (ML) has caused a fundamental change in how the society views medicine especially with the birth of telemedicine [16], early prognosis/diagnosis [17], Internet of Medical things [17]–[19], disease prediction [20], classification of medical images [21], [22], and others [23], [24], etc. ML has successfully proven that it has the capacity to identify patterns from large datasets, provide accurate predictions, and proffer promising and reliable solutions [25]–[27]. The core of ML is in its innate capability to analyze vast amount of data – so as to effectively identify and comprehend intricate patterns that may go unnoticed. Its use of historic dataset grants it the capability to yield algorithms that can accurately forecast future states in mental health disorder [28], [29]. Thus, ML schemes can be successfully trained to effectively recognize disease via pattern(s) detection – as they learn to classify the underlying features of interest, and to quickly detect unusual activities with patterns indicated as anomalous profile [30].

A variety of machine learning (ML) approaches successfully implemented on a variety of domain tasks. These include (but not limited to) the following: Logistic Regression [31]–[33], Deep Learning [34]–[36], Bayesian network [37]–[39], Support Vector Machine [40]–[42], K-Nearest Neighbors [43], Random Forest [44]–[46], and others [46]–[48].

While, it may be a known feat that many of these machine learning schemes have their inherent drawbacks – especially with feature selection technique and its prediction accuracy for the domain task. For this study – we adopt the multi-layer perceptron (MLP) network due to its capability to reduce overfitting, address imbalanced datasets, and yield a vigorous prediction accuracy [49].

1.1. Feedforward Networks

The integration of machine learning (ML) into healthcare has continued to revolutionize as a new paradigm and frontiers, innovative solutions to address intricate medical tasks. Our study seeks to harness integration of MLP to healthcare [50]. Our choice of MLP includes: (a) flexibility of the framework to yield great computation insight to analyzing complex data, (b) it can integrate diverse sources [51], and (c) framework can facilitate personalized interventions by adequately capturing intricate relations within mental health dataset that will enable tailored treatment planning based on individual characteristics [52].

Also, MLPs can detect subtle changes over time, allowing for early detection and risk prediction, which will in turn – yield improved outcome [53], [54]. Its robustness and adaptability to multimodal objective function further enhances its use in real-time monitoring and personalized healthcare delivery [55]. Thus, it has since become a veritable tool to address the many different complexities in mental health [56].

Other known reasons for its adoption includes:

1. Ease in Learning Complex Patterns: MLPs consists of interconnected nodes that can decode intrinsic patterns from (un)structured dataset – which the health record dataset is often characterized extensively thereof. MLPs can effectively learn subtle dynamisms and changes, chaotic and complex relations, correlations of bias and variances, which pivotal feats required in precise prognosis and early diagnosis [57].
2. Adaptability/Scalability to Diverse Format: Healthcare records and dataset often encompasses a plethora of formats. MLPs are both robust and flexible enough to handle a variety of (or heterogenous) dataset [58]. Even with the veracity of datasets in its sheer size and complexity, the architecture of the MLP is suited to gracefully grow to accommodate large datasets without degrading its performance. Additionally, it explores techniques such as dropout regularization, batch normalization and back-propagation learning as modes to bolster its resilience against overfit and poor generalization [59].
3. Applications Across Healthcare Domains: MLP has been successfully used in a variety of healthcare tasks ranging from diagnostic medicine, disease detection and classification, analyzing medical images with high precision, tailored treatment plans, predict disease progression, and discern optimal therapeutic interventions. Also, MLP has been used in expedited drug discovery and development processes, and also facilitated forecast in drug-target interactions [60].

The inherent gaps in previous studies includes thus.

1. Lack of Localized Datasets: Finding the right-format dataset within your locale – is crucial to ML task. And access to such high-quality dataset is needed in training and performance evaluation [61] as many healthcare facilities have policies of non-disclosure of data even for research. This often limits the available data, and also increases the chance of significant false positives in studies [62]–[65].

2. Cross-Channel Detection: With the evolution of telemedicine, the veracity of medical records generated across a variety of platforms as patient transaction has necessitated the increased use of multiple channels [66]–[68]. Thus, newer models must integrate the varying channel data to enhance the overall accuracy. Cross-channel telemedicine and mental health detection has now become a critical area of research and focus [69]–[71] as traditional mode may not yield cost-effective solutions (for onsite).

1.2. Related Works: Machine Learning and Mental Health Disorder

Mental health diagnosis has evolved to incorporate genetics, neuroscience, and societal shocks. Studies have shown that evolution of mental health is viewed from the various stages of man's life [72] as this disorder starts off in a man's first 30-years [73]. WHO notes that the diseases starts a year before the 15th year of any patient [74]. Turkey has recorded history of the disorder [52], which attracted attention from 19th-to-mid-20th-Century. Various schemes were used in its treatment such as exorcism, trepanation, and bloodletting [75].

The birth of psychotropics, marked the 20th-century strides in mental health care [55]. Today, experts have sought the use of machine learning techniques such as KNN, SVM, Decision tree, Random Forest, etc – with most of these schemes yielding an accuracy of of 81.22% [76].

The Gaussian Mixture Models (GMMs) can be used effectively on clustering behavioral data [51] to understand mental health patterns [77]. ML has been successfully in identifying serious symptoms in a patient, both for early diagnosis and in the formation of personalized therapy [78]. [79] predicted mental health disorders using XGBoost as early detection tool for the disease. [80] compared five machine-learning techniques and found that the Stacking technique had the highest accuracy in predicting mental health.

[77] reviewed ML algorithms used in diagnosing mental health; And identified SVM, GBM, and Random Forest – as most frequently used. Thus, many studies have suggested that ML have the potential to aid early detection of mental health. Also, study emphasizes the importance of early detection in improving outcomes and providing timely care for mental health disorders in young individuals.

2. MATERIAL AND METHOD

2.1. Data Gathering

Dataset was obtained from [web]: kaggle.com/datasets/bhavikjikadara/mental-health-dataset". It contains psychological indicators derived from post and test data from 2022. Its input feats consist of 292,364 records [76], [80]–[83] as in Table 1.

Table 1. Dataset Description for Cross-Channel Data Acquisition

Features	Data-Type	Format	Feature Description
Timestamp	Time	12:34	Time for attending to a patient case
Gender	Object	abcd	Gender or sex of the patient
Country	Object	abcd	Specifies the nationality of the patient
Occupation	Object	abcd	Specifies the kind of work the patient engages in
Self_employed	Boolean	0/1	Specifies if the patient is self-employed or not
Family_History	Boolean	0/1	Specifies if there are family traces of mental health disorder
Treatment	Object	abcd	Specifies if there has been related treatment to mental health disorder
Day_Indoors	Object	abcd	Duration from last transaction to the current transaction
Growing_Stress	Boolean	0/1	Specifies if a transaction is declined or not
Change_Habits	Boolean	0/1	Total transactions declined each day
Mental_Health_History	Boolean	0/1	Specifies if history of mental health disorder is in family or relation
Mood_Swings	Object	abcd	Specifies the occurrence of mood swing in patient
Coping_Struggles	Boolean	0/1	Specifies if patient has coping mechanism for stress and mental health
Work_Interest	Boolean	0/1	Specifies if patent has any interest in work that relieves stress
Social_Weakness	Object	abcd	Specifies if patient seeks and needy about emotional support and care
Mental_health_interview	object	abcd	Specifies if patient has been previously interviewed for mental health
Care_Options	Boolean	0/1	Specifies if patient has care support options like family and relatives
Mental_Health	Boolean	0/1	Set as 1 if transaction is True; Else set as 0 if False

2.2. The Proposed Genetic Algorithm Trained Neural Network (GANN)

It is known fact that hybrid (reinforcement) ensembles are always proven to better than single models. There is however, the issue of resolving conflicts that arise from encoding data as data flows and is transcribed from one heuristic to another. There is also the issue of structural dependencies imposed on the ensemble. These must be adequately and effectively resolved. We use a hybrid model as in figure 1 with 3-blocks [84] as thus: (a) a modular Kohonen neural network [46], (b) the supervised cultural genetic algorithm, and (c) a knowledge base.

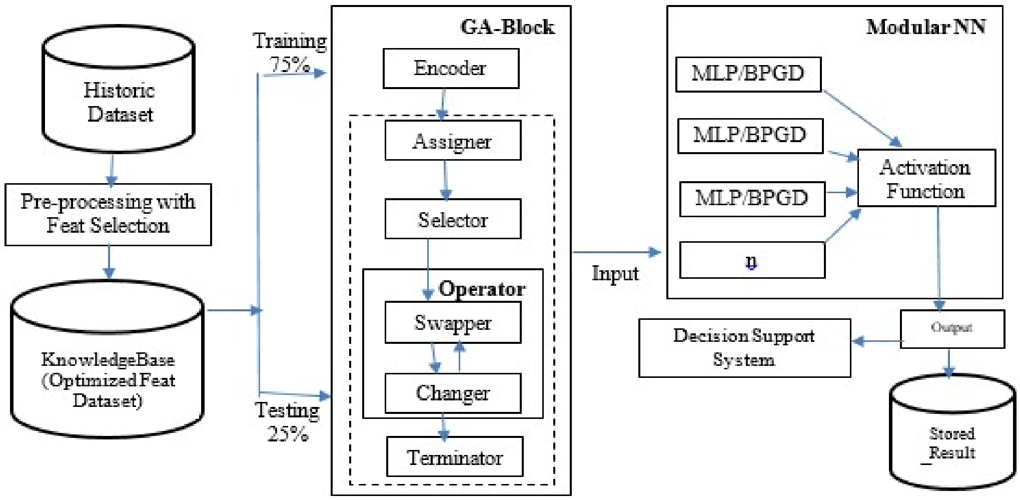

Figure 1. Hybrid Genetic Algorithm Trained Modular Neural Network Ensemble

1. The Cultural Genetic Algorithm (CGA): Basically, a GA-block uses 4 operators (initialize, fitness function and select, mutation, and crossover) to uncover probable solution(s). A gene is fit – if its value is close to the optimal. A variant of GA is CGA. It uses 4-belief spaces to define its solution space as: (a) the normative belief which defines the specific value ranges to which a gene is bound, (b) domain belief contains knowledge about the task being undertaken, (c) temporal belief contains knowledge about the available problem space, and (d) spatial belief contains knowledge about the topography for the task. Furthermore, it uses the influence function to bridge the belief spaces and the gene pool – to ensure any modified genes still conform to the belief space(s). The CGA should yield a result pool that does not violate its belief space and assist in reducing the number of potential genes generated by the GA until an optimum is discovered [76], [85], [86].
2. The Kohonen Modular Network (MNN) is a grid-like, feed-forward network whose first layer accepts input, and re-sends unbound to its second layer, which uses the transfer function to offer competitive computation. The competitive layer then maps similarity patterns into relations. Pattern relations noticed are used to determine the result after training [84]. We modify the parameters and carefully create our deep-learning Kohonen MNN through a deep architecture. Our learning is achieved by training the network component via 2-stages namely the pre-trained, and fine-tuned processes as described in [47], [87]. The MLP is a subtype of feedforward neural network that contains one or more hidden layers between the input and output layers. This MLP ensemble predicts results from dataset processing, to improve the entire accuracy of a system and reduce overfitting. Each layer in an MLP is composed of perceptions interconnected with weighted connections. The perceptions in each layer apply an activation function to the weighted sum of their inputs to produce an output, which serves as the input to the next layer. MLPs use backpropagation, a supervised learning technique which makes it distinct from other machine learning algorithm, to adjust the weights of the connections between neurons during training, optimizing the network to minimize prediction errors.

3. RESULTS AND DISCUSSION

3.1. Ensemble Performance

The figure 2 shows confusion matrix as with [88], [89] yielding outlier effects which also agrees with [20], [30], [90], [91] that the experimental GANN outperformed other benchmark models as it was best in its ability to successfully balance accuracy, recall, and precision. It also supports the effectiveness and efficiency of the hybrid ensemble – offering a detailed perspective of the ensemble's performance in differentiating between genuine positives, true negatives, false positives, and false negatives as in figure 2.

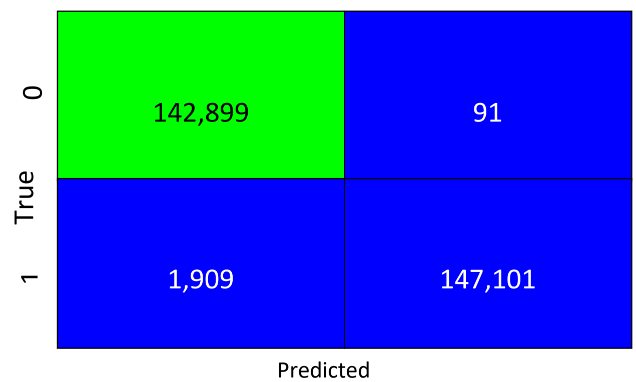

Figure 2. Hybrid Ensemble Confusion Matrix

Table 2. Performance metrics with Benchmark models

ML Schemes	F1	Accuracy	Precision	Recall
Random Forest	98.05	98.35	98.05	98.05
Decision Tree	92.10	96.28	90.18	94.48
XGBoost	91.25	96.74	96.16	85.90
Support Vector Machine	81.45	92.24	85.41	75.81
Proposed Hybrid GANN	99.19	99.91	98.28	98.10

Our experimental GANN ensemble was found to outperform other ensembles achieving an F1-score of 99.19% [92]; while, other ensembles like Random Forest, Decision Tree, XGBoost and Support Vector Machine – resulted and yielded an F1-score of 98.05%, 92.1%, 91.25% and 81.45% respectively [93]–[95]. In addition, the hybrid ensemble yielded an accuracy of 99. 91%; while, other ensembles (i.e. the Random Forest, Decision Tree, XGBoost and Support Vector Machine) yielded in an accuracy of 98.35%, 96.28%, 96.74%, and 92.24% respectively. It is clearly observed the experimental GANN ensured improved accuracy when compared with the results yielded in the studies as in Table 3, which agrees with [96]–[98].

3.2. Discussion of Findings

It provides insights into which characteristics have a bigger influence on overall performance and aids in identifying the most important aspects influencing the model's predictions [99]. Knowledge of the relative relevance of input variables in the predictive model requires a knowledge of feature importance, which is frequently established by statistical or computational analysis [100].

Our solution yielded a total of 56-rules with top rules found to have classification accuracy range [0.8, 0.96]. This implies that an estimated over 80% of the rules can adequately classify the dataset. Achieving a set of good rules, is much better than a single optimum rule [101]. This increases the chances of detecting malicious data packets as well as also improves the generality of rules, providing the ability for new dataset and their corresponding generated rules to be added to the knowledgebase [45], [102].

4. Conclusions

With the current surge in technological development and the widespread adoption of new technology-driven business strategies, businesses can now operate more efficiently, productively, and profitably. Despite the enormous amount of data generated daily, we have observed that the healthcare industry has always kept up-to-date with technology; However, the adoption of data analytics and data science will bolster the field of medicine. So, for the future of this industry, this study is a positive step and should be improved upon.

Furthermore, this research work signifies a paradigm shift in the application of artificial intelligence to mental health diagnostics. The combination of sophisticated Feed-forward neural networks like the multi-layer perceptron architecture, diverse datasets, and meticulous optimization techniques yields a robust framework for the accurate and timely detection of mental health disorders. As we continue to refine and expand upon these findings, the future holds immense promise for improved mental health outcomes through the integration of cutting-edge technology.

Author Contributions:
- Conceptualization: M.I. Akazue, and A.E Oweimieotu
- Methodology: M.I. Akazue, and C.Asuai
- Software and validation: A.E. Oweimieotu., M.I. Akazue and C.Asuai
- Formal analysis: A.Edje
- Investigation: X.X.; Resources and data curation: A.E Oweimieotu
- Writing original draft preparation: A.E. Oweimieotu
- Writing review and editing: M.I. Akazue
- Visualization: supervision: M.I. Akazue
- Project administration: M.I. Akazue and A. Edje
- Funding acquisition: A.E. Oweimieotu

REFERENCES

[1] J. Chung and J. Teo, “Mental Health Prediction Using Machine Learning: Taxonomy, Applications, and Challenges,” *Appl. Comput. Intell. Soft Comput.*, vol. 2022, 2022, doi: 10.1155/2022/9970363.

[2] R. R. Bond, M. D. Mulvenna, C. Potts, S. O’Neill, E. Ennis, and J. Torous, “Digital transformation of mental health services,” *npj Ment. Heal. Res.*, vol. 2, no. 1, pp. 1–9, 2023, doi: 10.1038/s44184-023-00033-y.

[3] C. Seiferth *et al.*, “How to e-mental health: a guideline for researchers and practitioners using digital technology in the context of mental health,” *Nat. Ment. Heal.*, vol. 1, no. 8, pp. 542–554, 2023, doi: 10.1038/s44220-023-00085-1.

[4] S. Gurjar *et al.*, “Mental Health Prediction Using Machine Learning,” pp. 1117–1121, 2022.

[5] W. Dc, “A custom publication of the Disease Control Priorities Project,” *Contraception*, vol. 30, No. January 2006, pp. 20–75, 2006.

[6] J. Kim, D. Kim, and R. Kamphaus, “Early Detection of Mental Health Through Universal Screening at Schools,” *Georg. Educ. Res.*, vol. 19, no. 1, 2022, doi: 10.20429/ger.2022.190104.

[7] B. Ojeme, M. Akazue, E. Nwelih, S. Africa, and C. Science, “Automatic Diagnosis of Depressive Disorders using Ensemble Techniques 1,” vol. 8, no. 3, pp. 31–38, 2016.

[8] A. Maureen, C. Asuai, A. Edje, E. Omede, and U. Emmanuel, “Cybershield: harnessing ensemble feature selection technique for robust distributed denial of service attacks detection,” *J. Adv. Comput. Commun. Inf. Technol.*, vol. 38, no. 03, pp. 1211–1224, 2023.

[9] R. A. Rahman, K. Omar, S. A. M. Noah, M. S. N. M. Danuri, and M. A. Al-Garadi, “Application of machine learning methods in mental health detection: A systematic review,” *IEEE Access*, vol. 8, pp. 183952–183964, 2020, doi: 10.1109/ACCESS.2020.3029154.

[10] K. Vaishnavi, U. N. Kamath, B. A. Rao, and N. V. S. Reddy, “Predicting Mental Health Illness using Machine Learning Algorithms,” *J. Phys. Conf. Ser.*, vol. 2161, no. 1, 2022, doi: 10.1088/1742-6596/2161/1/012021.

[11] A. I. Ben, A. M. I, and O. C. O, “Ant Colony Optimization Algorithm Based Vehicle Theft Prediction-Prevention and Recovery System Model (Aco-Vtp 2 rsm),” vol. 7, no. 06, pp. 251–260, 2016.

[12] A. A. Ojugo *et al.*, “Forging a User-Trust Memetic Modular Neural Network Card Fraud Detection Ensemble: A Pilot Study,” *J. Comput. Theor. Appl.*, vol. 1, no. 2, pp. 1–11, Oct. 2023, doi: 10.33633/jcta.v1i2.9259.

[13] A. A. Ojugo *et al.*, “Forging a learner-centric blended-learning framework via an adaptive content-based architecture,” *Sci. Inf. Technol. Lett.*, vol. 4, no. 1, pp. 40–53, May 2023, doi: 10.31763/sitech.v4i1.1186.

[14] O. D. Voke, A. Maureen, and I. Anthony, “A Framework for Feature Selection using Data Value Metric and Genetic Algorithm,” vol. 184, no. 43, pp. 14–21, 2023.

[15] A. Maureen, O. Oghenefego, A. E. Edje, and C. O. Ogeh, “An Enhanced Model for the Prediction of Cataract Using Bagging Techniques,” vol. 8, no. 2, 2023.

[16] A. A. Ojugo and O. D. Otakore, “Improved Early Detection of Gestational Diabetes via Intelligent Classification Models: A Case of the Niger Delta Region in Nigeria,” *J. Comput. Sci. Appl.*, vol. 6, no. 2, pp. 82–90, 2018, doi: 10.12691/jcsa-6-2-5.

[17] S. R. Guntur, R. R. Gorrepati, and V. R. Dirisala, “Internet of Medical Things,” *Med. Big Data Internet Med. Things*, no. February, pp. 271–297, Oct. 2018, doi: 10.1201/9781351030380-11.

[18] S. Og and L. Ying, “The Internet of Medical Things,” *ICMLCA 2021 - 2nd Int. Conf. Mach. Learn. Comput. Appl.*, pp. 273–276, 2021.

[19] K. Kakhi, R. Alizadehsani, H. M. D. Kabir, A. Khosravi, S. Nahavandi, and U. R. Acharya, “The internet of medical things and artificial intelligence: trends, challenges, and opportunities,” *Biocybern. Biomed. Eng.*, vol. 42, no. 3, pp. 749–771, 2022, doi: 10.1016/j.bbe.2022.05.008.

[20] F. Mustofa, A. N. Safriandono, A. R. Muslikh, and D. R. I. M. Setiadi, “Dataset and Feature Analysis for Diabetes Mellitus Classification using Random Forest,” *J. Comput. Theor. Appl.*, vol. 1, no. 1, pp. 41–48, 2023, doi: 10.33633/jcta.v1i1.9190.

[21] M. S. Sunarjo, H.-S. Gan, and D. R. I. M. Setiadi, “High-Performance Convolutional Neural Network Model to Identify COVID-19 in Medical Images,” *J. Comput. Theor. Appl.*, vol. 1, no. 1, pp. 19–30, 2023, doi: 10.33633/jcta.v1i1.8936.

[22] A. A. Ojugo and E. O. Ekurume, “Predictive Intelligent Decision Support Model in Forecasting of the Diabetes Pandemic Using a Reinforcement Deep Learning Approach,” *Int. J. Educ. Manag. Eng.*, vol. 11, no. 2, pp. 40–48, Apr. 2021, doi: 10.5815/ijeme.2021.02.05.

[23] O. D. Voke, M. I. Akazue, E. U. Omede, E. . Oboh, and A. . Imianvan, “Survival Prediction of Cervical Cancer Patients using Genetic Algorithm-Based Data Value Metric and Recurrent Neural Network,” *Int. J. Soft Comput. Eng.*, vol. 13, no. 2, pp. 29–41, May 2023, doi: 10.35940/ijsce.B3608.0513223.

[24] E. . Ihama, M. I. Akazue, E. U. Omede, and D. V. Ojie, “A Framework for Smart City Model Enabled by Internet of Things (IoT),” *Int. J. Comput. Appl.*, vol. 185, no. 6, pp. 6–11, 2023, doi: 10.5120/ijca2023922685.

[25] H. Hasan, A. H. Harun, and Z. S. M. Rashid, “Factors That Influence Online Purchase Intention Of Online Brand,” *Conf. Pap.*, vol. 16, no. 10, pp. 1–10, 2018.

[26] C. Panwar, “Consumer perceived risk in online shopping environment via Facebook as medium,” *Int. J. Eng. Technol.*, vol. 7, no. 4, pp. 2485–2490, 2018, doi: 10.14419/ijet.v7i4.11017.

[27] A. A. Ojugo and R. E. Yoro, “Computational Intelligence in Stochastic Solution for Toroidal N-Queen,” *Prog. Intell. Comput. Appl.*, vol. 1, no. 2, pp. 46–56, 2013, doi: 10.4156/pica.vol2.issue1.4.

[28] A. A. Ojugo, A. O. Eboka, R. E. Yoro, M. O. Yerokun, and F. N. Efozia, “Framework design for statistical fraud detection,” *Math. Comput. Sci. Eng. Ser.*, vol. 50, pp. 176–182, 2015.

[29] I. P. Okobah and A. A. Ojugo, “Evolutionary Memetic Models for Malware Intrusion Detection: A Comparative Quest for Computational Solution and Convergence,” *Int. J. Comput. Appl.*, vol. 179, no. 39, pp. 34–43, 2018, doi: 10.5120/ijca2018916586.

[30] A. R. Muslikh, I. D. R. M. Setiadi, and A. A. Ojugo, “Rice disease recognition using transfer xception convolution neural network,” *J. Tek. Inform.*, vol. 4, no. 6, pp. 1541–1547, 2023, doi: 10.52436/1.jutif.2023.4.6.1529.

[31] E. Ileberi, Y. Sun, and Z. Wang, “A machine learning based credit card fraud detection using GA algorithm for feature selection,” *J. Big Data*, vol. 9, no. 1, p. 24, Dec. 2022, doi: 10.1186/s40537-022-00573-8.

[32] R. E. Yoro, F. O. Aghware, M. I. Akazue, A. E. Ibor, and A. A. Ojugo, “Evidence of personality traits on phishing attack menace among selected university undergraduates in Nigerian,” *Int. J. Electr. Comput. Eng.*, vol. 13, no. 2, p. 1943, Apr. 2023, doi: 10.11591/ijece.v13i2.pp1943-1953.

[33] C. Li, N. Ding, H. Dong, and Y. Zhai, “Application of Credit Card Fraud Detection Based on CS-SVM,” *Int. J. Mach. Learn. Comput.*, vol. 11, no. 1, pp. 34–39, 2021, doi: 10.18178/ijmlc.2021.11.1.1011.

[34] I. Benchaji, S. Douzi, B. El Ouahidi, and J. Jaafari, “Enhanced credit card fraud detection based on attention mechanism and LSTM deep model,” *J. Big Data*, vol. 8, no. 1, p. 151, Dec. 2021, doi: 10.1186/s40537-021-00541-8.

[35] A. A. Ojugo and R. E. Yoro, “Forging a deep learning neural network intrusion detection framework to curb the distributed denial of service attack,” *Int. J. Electr. Comput. Eng.*, vol. 11, no. 2, pp. 1498–1509, 2021, doi: 10.11591/ijece.v11i2.pp1498-1509.

[36] F. O. Aghware, R. E. Yoro, P. O. Ejeh, C. C. Odiakaose, F. U. Emordi, and A. A. Ojugo, “DeLClustE: Protecting Users from Credit-Card Fraud Transaction via the Deep-Learning Cluster Ensemble,” *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 6, pp. 94–100, 2023, doi: 10.14569/IJACSA.2023.0140610.

[37] L. E. Mukhanov, “Using bayesian belief networks for credit card fraud detection,” *Proc. IASTED Int. Conf. Artif. Intell. Appl. AIA 2008*, no. February 2008, pp. 221–225, 2008.

[38] A. A. Ojugo and A. O. Eboka, “Empirical Bayesian network to improve service delivery and performance dependability on a campus network,” *IAES Int. J. Artif. Intell.*, vol. 10, no. 3, p. 623, Sep. 2021, doi: 10.11591/ijai.v10.i3.pp623-635.

[39] A. A. Ojugo and O. D. Otakore, “Forging An Optimized Bayesian Network Model With Selected Parameters For Detection of The Coronavirus In Delta State of Nigeria,” *J. Appl. Sci. Eng. Technol. Educ.*, vol. 3, no. 1, pp. 37–45, Apr. 2021, doi: 10.35877/454RI.asci2163.

[40] E. R. Altman, "Synthesizing Credit Card Transactions," *PeerJ Comput. Sci.*, vol. 14, Oct. 2019, [Online]. Available: http://arxiv.org/abs/1910.03033

[41] A. A. Ojugo and D. A. Oyemade, "Boyer moore string-match framework for a hybrid short message service spam filtering technique," *IAES Int. J. Artif. Intell.*, vol. 10, no. 3, pp. 519–527, 2021, doi: 10.11591/ijai.v10.i3.pp519-527.

[42] M. I. Akazue, R. E. Yoro, B. O. Malasowe, O. Nwankwo, and A. A. Ojugo, "Improved services traceability and management of a food value chain using block-chain network : a case of Nigeria," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 29, no. 3, pp. 1623–1633, 2023, doi: 10.11591/ijeecs.v29.i3.pp1623-1633.

[43] E. A. L. Marazqah Btoush, X. Zhou, R. Gururajan, K. C. Chan, R. Genrich, and P. Sankaran, "A systematic review of literature on credit card cyber fraud detection using machine and deep learning," *PeerJ Comput. Sci.*, vol. 9, p. e1278, Apr. 2023, doi: 10.7717/peerj-cs.1278.

[44] S. Xuan, G. Liu, Z. Li, L. Zheng, S. Wang, and C. Jiang, "Random forest for credit card fraud detection," in *2018 IEEE 15th International Conference on Networking, Sensing and Control (ICNSC)*, IEEE, Mar. 2018, pp. 1–6. doi: 10.1109/ICNSC.2018.8361343.

[45] M. I. Akazue, C. Asuai, A. E. Edje, and E. Omede, "Cybershield: harnessing ensemble feature selection technique for robust distributed denial of service," *Kongzhi yu Juece/Control Decis.*, vol. 38, no. August, pp. 1211–1224, 2023.

[46] A. A. Ojugo and O. Nwankwo, "Spectral-Cluster Solution For Credit-Card Fraud Detection Using A Genetic Algorithm Trained Modular Deep Learning Neural Network," *JINAV J. Inf. Vis.*, vol. 2, no. 1, pp. 15–24, Jan. 2021, doi: 10.35877/454RI.jinav274.

[47] Y. Abakarim, M. Lahby, and A. Attioui, "An Efficient Real Time Model For Credit Card Fraud Detection Based On Deep Learning," in *International Conference on Intelligent Systems*, New York, NY, USA: ACM, Oct. 2018, pp. 1–7. doi: 10.1145/3289402.3289530.

[48] M. Zareapoor and P. Shamsolmoali, "Application of Credit Card Fraud Detection: Based on Bagging Ensemble Classifier," *Procedia Comput. Sci.*, vol. 48, pp. 679–685, 2015, doi: 10.1016/j.procs.2015.04.201.

[49] C. Wright and A. Serguieva, "Sustainable blockchain-enabled services: Smart contracts," in *2017 IEEE International Conference on Big Data (Big Data)*, IEEE, Dec. 2017, pp. 4255–4264. doi: 10.1109/BigData.2017.8258452.

[50] A. S. Pillai, "Multi-Label Chest X-Ray Classification via Deep Learning," *J. Intell. Learn. Syst. Appl.*, vol. 14, pp. 43–56, 2022, doi: 10.4236/jilsa.2022.144004.

[51] C. C. Bennett, M. K. Ross, E. G. Baek, D. Kim, and A. D. Leow, "Smartphone accelerometer data as a proxy for clinical data in modeling of bipolar disorder symptom trajectory," *npj Digit. Med.*, vol. 5, no. 1, pp. 1–10, 2022, doi: 10.1038/s41746-022-00741-3.

[52] M. K. Bilir and F. Artvinli, "The history of mental health policy in Turkey: tradition, transition and transformation," *Hist. Psychiatry*, vol. 32, no. 1, pp. 3–19, 2021, doi: 10.1177/0957154X20966178.

[53] S. Busuttil, "Support Vector Machines (SVM) Support Vector Machines (SVM)," *Gesture*, vol. 23, no. 6, pp. 349–361, 2001.

[54] F. Balducci, D. Impedovo, and G. Pirlo, "Machine Learning Applications on Agricultural Datasets for Smart Farm Enhancement," *Machines*, vol. 6, no. 3, p. 38, Sep. 2018, doi: 10.3390/machines6030038.

[55] J. T. Braslow and S. R. Marder, "History of Psychopharmacology," *Annu. Rev. Clin. Psychol.*, vol. 15, pp. 25–50, 2019, doi: 10.1146/annurev-clinpsy-050718-095514.

[56] A. A. Ojugo *et al.*, "CoSoGMIR: A Social Graph Contagion Diffusion Framework using the Movement-Interaction-Return Technique," *J. Comput. Theor. Appl.*, vol. 1, no. 2, pp. 37–47, 2023, doi: 10.33633/jcta.v1i2.9355.

[57] M. K. G. Roshan, "Multiclass Medical X-ray Image Classification using Deep Learning with Explainable AI," *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 10, no. 6, pp. 4518–4526, Jun. 2022, doi: 10.22214/ijraset.2022.44541.

[58] A. A. Ojugo and O. D. Otakore, “Intelligent cluster connectionist recommender system using implicit graph friendship algorithm for social networks,” *IAES Int. J. Artif. Intell.*, vol. 9, no. 3, p. 497~506, 2020, doi: 10.11591/ijai.v9.i3.pp497-506.
[59] D. A. Oyemade *et al.*, “A Three Tier Learning Model for Universities in Nigeria,” *J. Technol. Soc.*, vol. 12, no. 2, pp. 9–20, 2016, doi: 10.18848/2381-9251/CGP/v12i02/9-20.
[60] J. K. Oladele *et al.*, “BEHeDaS: A Blockchain Electronic Health Data System for Secure Medical Records Exchange,” *J. Comput. Theor. Appl.*, vol. 2, no. 1, pp. 1–12, 2024, doi: 10.33633/jcta.v2i19509.
[61] E. Omede, J. Anenechukwu, and C. Hampo, “Use of Adaptive Boosting Algorithm to Estimate User’s Trust in the Utilization of Virtual Assistant Systems,” *Int. J. Innov. Sci. Res. Technol.*, vol. 8, no. 1, pp. 502–509, 2023.
[62] A. A. Ojugo and A. O. Eboka, “Comparative Evaluation for High Intelligent Performance Adaptive Model for Spam Phishing Detection,” *Digit. Technol.*, vol. 3, no. 1, pp. 9–15, 2018, doi: 10.12691/dt-3-1-2.
[63] B. N. Supriya and C. B. Akki, “Sentiment prediction using enhanced xgboost and tailored random forest,” *Int. J. Comput. Digit. Syst.*, vol. 10, no. 1, pp. 191–199, 2021, doi: 10.12785/ijcds/100119.
[64] S. Meghana, B. . Charitha, S. Shashank, V. S. Sulakhe, and V. B. Gowda, “Developing An Application for Identification of Missing Children and Criminal Using Face Recognition.,” *Int. J. Adv. Res. Comput. Commun. Eng.*, vol. 12, no. 6, pp. 272–279, 2023, doi: 10.17148/ijarcce.2023.12648.
[65] Sharmila, R. Sharma, D. Kumar, V. Puranik, and K. Gautham, “Performance Analysis of Human Face Recognition Techniques,” *Proc. - 2019 4th Int. Conf. Internet Things Smart Innov. Usages, IoT-SIU 2019*, no. May 2020, pp. 1–4, 2019, doi: 10.1109/IoT-SIU.2019.8777610.
[66] L. De Kimpe, M. Walrave, W. Hardyns, L. Pauwels, and K. Ponnet, “You’ve got mail! Explaining individual differences in becoming a phishing target,” *Telemat. Informatics*, vol. 35, no. 5, pp. 1277–1287, Aug. 2018, doi: 10.1016/j.tele.2018.02.009.
[67] K. Deepika, M. P. S. Nagenddra, M. V. Ganesh, and N. Naresh, “Implementation of Credit Card Fraud Detection Using Random Forest Algorithm,” *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 10, no. 3, pp. 797–804, Mar. 2022, doi: 10.22214/ijraset.2022.40702.
[68] J. R. Amalraj and R. Lourdusamy, “A Novel distributed token-based algorithm using secret sharing scheme for secure data access control,” *Int. J. Comput. Networks Appl.*, vol. 9, no. 4, p. 374, Aug. 2022, doi: 10.22247/ijcna/2022/214501.
[69] P. Boulieris, J. Pavlopoulos, A. Xenos, and V. Vassalos, “Fraud detection with natural language processing,” *Mach. Learn.*, Jul. 2023, doi: 10.1007/s10994-023-06354-5.
[70] I. A. Anderson and W. Wood, “Habits and the electronic herd: The psychology behind social media’s successes and failures,” *Consum. Psychol. Rev.*, vol. 4, no. 1, pp. 83–99, Jan. 2021, doi: 10.1002/arcp.1063.
[71] Y. Kang, M. Ozdogan, X. Zhu, Z. Ye, C. Hain, and M. Anderson, “Comparative assessment of environmental variables and machine learning algorithms for maize yield prediction in the US Midwest,” *Environ. Res. Lett.*, vol. 15, no. 6, p. 064005, Jun. 2020, doi: 10.1088/1748-9326/ab7df9.
[72] A. Troisi, “The evolutionary diagnosis of mental disorder,” 2015, doi: 10.1002/wcs.1339.
[73] G. De Girolamo, J. Dagani, R. Purcell, A. Cocchi, and P. D. McGorry, “Age of onset of mental disorders and use of mental health services: needs, and obstacles,” *Epidemiol. Psychiatr. Sci.*, vol. 21, no. 1, pp. 47–57, 2012, doi: 10.1017/S2045796011000746.
[74] W. World Health Organization, “Mental health in primary care: illusion or inclusion?,” *World Heal. Organ.*, p. 18p, 2018.
[75] S. Rasquinha, A. Joe, and A. Safeekh, “Psychiatric treatment in the preneuroleptic era,” *Arch. Med. Heal. Sci.*, vol. 7, no. 2, p. 298, 2019, doi: 10.4103/amhs.amhs_159_19.

[76] F. O. Aghware, R. E. Yoro, P. O. Ejeh, C. C. Odiakaose, F. U. Emordi, and A. A. Ojugo, "Sentiment analysis in detecting sophistication and degradation cues in malicious web contents," *Kongzhi yu Juece/Control Decis.*, vol. 38, no. 01, p. 653, 2023.
[77] G. Cho, J. Yim, Y. Choi, J. Ko, and S. H. Lee, "Review of machine learning algorithms for diagnosing mental illness," *Psychiatry Investig.*, vol. 16, no. 4, pp. 262–269, 2019, doi: 10.30773/pi.2018.12.21.2.
[78] A. Sarkar, S. S. Mallik, and K. Roy, "Original Article A Survey of Machine Learning Based Methods for the Diagnosis of Mental HealthA Survey of Machine Learning Based Methods for the Diagnosis of Mental Health," vol. 3, no. 2, pp. 39–55, 2022.
[79] M. D. Ginsberg, "How Much Anguish is Enough ? Baby Switching and Negligent Infliction of Emotional Distress AND NEGLIGENT INFLICTION OF EMOTIONAL DISTRESS," vol. 13, no. 2, 2015.
[80] M. Srividya, S. Mohanavalli, and N. Bhalaji, "Behavioral Modeling for Mental Health using Machine Learning Algorithms," *J. Med. Syst.*, vol. 42, no. 5, 2018, doi: 10.1007/s10916-018-0934-5.
[81] S. S. Verma *et al.*, "Collective feature selection to identify crucial epistatic variants," *BioData Min.*, vol. 11, no. 1, p. 5, Dec. 2018, doi: 10.1186/s13040-018-0168-6.
[82] S. Do, K. D. Song, and J. W. Chung, "Basics of Deep Learning : A Radiologist ' s Guide to Understanding Published Radiology Articles on Deep Learning," *Korean J. Radiol.*, vol. 21, no. 1, pp. 33–41, 2020, doi: 10.3348/kjr.2019.0312.
[83] M. I. Akazue, A. A. Ojugo, R. E. Yoro, B. O. Malasowe, and O. Nwankwo, "Empirical evidence of phishing menace among undergraduate smartphone users in selected universities in Nigeria," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 28, no. 3, pp. 1756–1765, Dec. 2022, doi: 10.11591/ijeecs.v28.i3.pp1756-1765.
[84] G. Behboud, "Reasoning using Modular Neural Network," *Towar. Data Sci.*, vol. 34, no. 2, pp. 12–34, 2020.
[85] X. Lin, P. R. Spence, and K. A. Lachlan, "Social media and credibility indicators: The effect of influence cues," *Comput. Human Behav.*, vol. 63, pp. 264–271, Oct. 2016, doi: 10.1016/j.chb.2016.05.002.
[86] S. M. Albladi and G. R. S. Weir, "User characteristics that influence judgment of social engineering attacks in social networks," *Human-centric Comput. Inf. Sci.*, vol. 8, no. 1, p. 5, Dec. 2018, doi: 10.1186/s13673-018-0128-7.
[87] R. J. Urbanowicz, M. Meeker, W. La Cava, R. S. Olson, and J. H. Moore, "Relief-based feature selection: Introduction and review," *J. Biomed. Inform.*, vol. 85, pp. 189–203, Sep. 2018, doi: 10.1016/j.jbi.2018.07.014.
[88] G. TekalignTujo, G. Dileep Kumar, D. ElifeneshYitagesu, and B. MeseretGirma, "Predictive Model to Predict Seed Classes using Machine Learning," *Int. J. Eng. Res. \& Technol.*, vol. 6, no. 08, pp. 334–344, 2017.
[89] Q. Li *et al.*, "An Enhanced Grey Wolf Optimization Based Feature Selection Wrapped Kernel Extreme Learning Machine for Medical Diagnosis," *Comput. Math. Methods Med.*, vol. 2017, pp. 1–15, 2017, doi: 10.1155/2017/9512741.
[90] E. U. Omede, A. Edje, M. I. Akazue, H. Utomwen, and A. A. Ojugo, "IMANoBAS: An Improved Multi-Mode Alert Notification IoT-based Anti-Burglar Defense System," *J. Comput. Theor. Appl.*, vol. 2, no. 1, pp. 43–53, 2024, doi: 10.33633/jcta.v2i1.9541.
[91] C. C. Odiakaose, F. U. Emordi, P. O. Ejeh, O. Attoh, and N. C. Ashioba, "A pilot study to enhance semi-urban tele-penetration and services provision for undergraduates via the effective design and extension of campus telephony," *FUPRE J. Sci. Ind. Res.*, vol. 7, no. 3, pp. 35–48, 2023.
[92] A. E. Ibor, E. B. Edim, and A. A. Ojugo, "Secure Health Information System with Blockchain Technology," *J. Niger. Soc. Phys. Sci.*, vol. 5, no. 992, pp. 1–8, 2023, doi: 10.46481/jnsps.2022.992.

[93] R. E. Yoro, F. O. Aghware, B. O. Malasowe, O. Nwankwo, and A. A. Ojugo, "Assessing contributor features to phishing susceptibility amongst students of petroleum resources varsity in Nigeria," *Int. J. Electr. Comput. Eng.*, vol. 13, no. 2, p. 1922, Apr. 2023, doi: 10.11591/ijece.v13i2.pp1922-1931.
[94] A. Ali *et al.*, "Financial Fraud Detection Based on Machine Learning: A Systematic Literature Review," *Appl. Sci.*, vol. 12, no. 19, p. 9637, Sep. 2022, doi: 10.3390/app12199637.
[95] A. Shaji, S. Binu, A. M. Nair, and J. George, "Fraud Detection in Credit Card Transaction Using ANN and SVM," 2021, pp. 187–197. doi: 10.1007/978-3-030-79276-3_14.
[96] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," *J. Big Data*, vol. 6, no. 1, 2019, doi: 10.1186/s40537-019-0197-0.
[97] U. R. Wemembu, E. O. Okonta, A. A. Ojugo, and I. L. Okonta, "A Framework for Effective Software Monitoring in Project Management," *West African J. Ind. Acad. Res.*, vol. 10, no. 1, pp. 102–115, 2014.
[98] A. A. Ojugo and R. E. Yoro, "Extending 3-tier constructivist learning model for alternative delivery: ahead the COVID-19 pandemic in Nigeria," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 21, no. 3, p. 1673, Mar. 2021, doi: 10.11591/ijeecs.v21.i3.pp1673-1682.
[99] M. Armstrong and J. Vickers, "Patterns of Price Competition and the Structure of Consumer Choice," *MPRA Pap.*, vol. 1, no. 98346, pp. 1–40, 2020.
[100] A. A. Ojugo and R. E. Yoro, "Predicting Futures Price And Contract Portfolios Using The ARIMA Model: A Case of Nigeria's Bonny Light and Forcados," *Quant. Econ. Manag. Stud.*, vol. 1, no. 4, pp. 237–248, 2020, doi: 10.35877/454ri.qems139.
[101] M. I. Akazue, I. A. Debekeme, A. E. Edje, C. Asuai, and U. J. Osame, "Unmasking fraudsters: Ensemble Features Selection to Enhance Random Forest Fraud Detection," *J. Comput. Theor. Appl.*, vol. 1, no. 2, pp. 201–212, 2023, doi: 10.33633/jcta.v1i2.9462.
[102] F. U. Emordi, C. C. Odiakaose, P. O. Ejeh, O. Attoh, and N. C. Ashioba, "Student's Perception and Assessment of DOU-Asaba website for Academic Information Retrieval, Footprints and Usability," *FUPRE J. Sci. Ind. Res.*, vol. 7, no. 3, pp. 49–60, 2023.