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EXPLORING INDUSTRY 4.0: SENTIMENT ANALYSIS ON BEHAVIORAL ADOPTION OF e-NAIRA DIGITAL CURRENCY IN NIGERIA USING SVM AND XGBOOST MODELS

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ABSTRACT

This research investigates the influence of Industry 4.0, focusing on eNaira as a key component of this revolution. It examines adoption trends through the application of advanced machine learning techniques, emphasizing supervised and ensemble learning models. Industry 4.0 refers to the fourth industrial revolution, marked by the integration of advanced technologies like artificial intelligence (AI), the Internet of Things (IoT), robotics, big data, blockchain, and cloud computing into industrial processes. The eNaira is Nigeria's national digital currency, designed to promote financial inclusion and advance the country's cashless policy. Similar initiatives include eKrona in Sweden, eRupee in India, and eCNY in China. In this study, Support Vector Machines (SVM) Aand XGBoost are utilized to analyze public sentiment on eNaira adoption based on 1,254 entries from Twitter, Facebook, and Instagram, prominent platforms for public discourse. To ensure robust analysis, Natural Language Processing (NLP) techniques are applied to systematically clean, model, and interpret the data. Results indicate that while the SVM model achieved a respectable accuracy rate of 78%, XGBoost significantly outperformed it with an accuracy of 94%, demonstrating the ensemble method's effectiveness in capturing distinct patterns in public sentiment toward eNaira. These insights provide valuable guidance for policymakers, offering a deeper understanding of public perceptions that can inform strategies to enhance the revolution of industry 4.0 and the eNaira adoption among citizens in Nigeria.

Keywords: eNaira, Digital Currency, Machine Learning, Industry 4.0, Technology Adoption

1. INTRODUCTION

Today, Industry 4.0 explores applications across sectors such as manufacturing, healthcare, finance, and beyond, driving innovations like automation, predictive maintenance, and personalized services [1]. It prioritizes efficiency, sustainability, and innovation, transforming industries and economies worldwide [2]. Digital currency, a subset of blockchain technology, emerges as a significant application of Industry 4.0 [3]. The adoption of this digital paradigm is rapidly gaining momentum on a global scale, especially during the recent surge of the COVID-19 pandemic, there has been a global shift towards exploring contactless economies and lifestyles [4]. This shift has accelerated the automation of various sectors, including financial systems and applications, fostering the adoption of digital solutions to ensure seamless and safe transactions remotely and efficiently [5]. Countries like India, China, the Bahamas, and Nigeria have introduced their national digital currencies, known as the eRupee, eCNY, Sand Dollar, and eNaira, respectively [6]. These initiatives reflect a global trend toward embracing digital financial systems to enhance efficiency, inclusion, and innovation of the industry 4.0. The digital currency is an electronic version of a nation's hard currency that is designed to improve the nation's financial ecosystem, facilitate online transactions, and enhance financial inclusion [7]. As with any new technology, the introduction of the eNaira has sparked widespread public discourse and a range of opinions on the adoption of the eNaira among citizens, making sentiment analysis a crucial tool for evaluating public perceptions on the adoption of the eNaira digital currency [8].

The eNaira was launched on 25th October, 2021 during the covid 19 pandemic with the aim of enabling the majority of the individuals without bank accounts to perform online transactions using their mobile phone numbers [9]. This initiative is expected to reduce the number of unbanked citizens and speed up transaction processing time [9]. Furthermore, the implementation of the eNaira is anticipated to decrease corruption by minimizing physical cash transactions and improve financial inclusion in rural areas where bank branches are limited [10]. However, the Central Bank of Nigeria has expressed concerns about the low adoption of the eNaira among citizens [11]. According to the report by CBN, the eNaira, if fully adopted, could boost the Nigerian GDP by about 29 million USD over a decade [12]. According to a market estimate from early 2023, "Global digital currency platform transactions increased from $6.09 billion in 2022 to $6.9 billion in 2023, with a compound annual growth rate (CAGR) of 13.2%, and digital banking platform market is projected to grow to $11.34 billion by 2027, also at a CAGR of 13.2%" [13]. According to this report, transactions processed through central bank digital currencies are expected to increase by 260,000 percent between 2023 and 2030.

In Nigeria, the Central Bank has raised concerns about the high number of unbanked citizens [11]. Out of over 200 million people, only about 550,000 have a bank account [14]. This lack of financial inclusion prevents many Nigerians from accessing social intervention programs due to the absence of formal bank accounts, encourages corruption through the continued use of cash-based transactions, and increases governance costs due to the frequent printing of physical currency [15]. To address these challenges, Nigeria introduced the eNaira, the country's digital currency on 25th October 2021, with aims to modernize its financial infrastructure, improve financial inclusion, and encourage cashless transactions [16]. Despite these efforts, eNaira adoption has remained relatively low, especially among key demographics such as youth and students who forms the majority of the population in the country. Understanding the factors that influence eNaira adoption is essential for developing targeted strategies that can promote its wider adoption across different user groups.

Existing studies on digital currency adoption often focus on broad demographic and socio-economic factors, such as age, income, and education, along with technical elements like ease of use, perceived security, and accessibility [17], [18], [19]. These studies typically use traditional statistical methods, which, while effective to a degree, may fall short in identifying the complex, nonlinear relationships that exist between these variables. This limitation creates a gap, leveraging advanced machine learning approaches to gain a more advance understanding of the factors influencing eNaira adoption from the individual opinions. Machine learning algorithms like Support Vector Machines (SVM) and Extreme Gradient Boosting (XGBoost) are particularly advantageous for this purpose, as they excel at processing large datasets with intricate variable interactions [20], [21]. These models not only capture nonlinear relationships but also provide robust predictive capabilities, making them highly suitable for analyzing the unique adoption patterns of digital currencies such as the eNaira.

Sentiment analysis is commonly applied across various fields like linguistics, computer science, healthcare, and education [22].The novelty in this research lies in its application of multiple advanced machine learning models to sentiment analysis specifically within the context of a national digital currency, such as Nigeria's eNaira. This study stands out for using a variety of models, each with distinct benefits, to examine views about the adoption of a new digital currency in a particular setting. This method adds to the increasing corpus of knowledge about digital financial technology while also improving the sentiment analysis's adaptability and accuracy. Furthermore, by focusing on the relationship between sentiment analysis and the adoption of digital currencies, the study fills a gap in the literature and provides novel insights on how the public perceives and absorbs new financial technology. This study aims to explore the applications of industry 4.0 in the financial sector and to understand the determinants influencing public opinion on the adoption of the Nigerian eNaira digital currency by developing a predictive model. The findings will shed light on how the public feels about eNaira and add important information to the larger field of sentiment analysis in financial technology.

This study proposes integrating XGBoost and SVM machine learning algorithms to identify the key determinants of eNaira adoption in Nigeria, utilizing Twitter, Facebook and Instagram applications as the platforms for extracting the opinions of the Nigerian citizens on the eNaira digital currency. XGBoost, an ensemble method, is recognized for its high accuracy and efficiency with structured data, making it ideal for detecting subtle patterns and trends [23], [24]. And SVM is known for its strength in classification tasks, which is particularly effective in handling high-dimensional data, allowing it to

manage complex datasets with multiple influencing factors [24], [25]. By combining these techniques, the study seeks to improve predictive accuracy and model interpretability, providing a thorough analysis of the factors that affect eNaira adoption. This hybrid approach is expected to yield insights that could help policymakers and stakeholders better understand and address the eNaira adoption challenges.
The research aims to address two primary questions: (1) What are the key determinants of eNaira adoption among Nigerian citizens? and (2) What models are most effective for predicting eNaira adoption among these citizens? To explore these questions, the paper is organized as follows: Section One introduces the concept of digital currency and the rationale behind the eNaira. Section Two presents a review of relevant literature on digital currency adoption factors and previous modeling approaches. Section Three outlines the methodology, detailing the integration of XGBoost and SVM models. Section Four provides the results and discussion, examining findings in the context of the research questions. Finally, Section Five concludes with key insights and recommendations for future research directions.

2. LITERATURE REVIEW

2.1. The industry 4.0

The First Industrial Revolution, which took place between 1760 and 1840, marked a transformative period in human history [26]. It was characterized by the invention of the steam engine, which reduced reliance on manual and animal labor while automating key production processes. The Second Industrial Revolution, or Technological Revolution, occurred between 1870 and 1914, this era introduced electricity and several technological advancements, such as the assembly line, which facilitated large-scale mass production [27]. The Third Industrial Revolution, also known as the Digital Revolution, began in the 1950s with the advent of computers and gained momentum with the development of the Internet and digital technologies [28]. By 2015, this revolution had significantly automated manufacturing processes, setting the stage for the rise of Industry 4.0. The Fourth Industrial Revolution, or Industry 4.0, builds on the complete digitization of previous eras, integrating advanced technologies into production systems. While it is primarily focused on manufacturing, Industry 4.0 is reshaping every sector of the global economy, driving innovation and transformation across all business areas [26]. It is anticipated that the Fourth Industrial Revolution will accelerate digital transformation, leading to a comprehensive restructuring of business operations and the establishment of digital cultures within organizations.

Industry 4.0 represents a significant paradigm shift, transitioning from traditional analog systems to highly automated and innovative platforms across a wide range of sectors. This transformation encompasses industries such as finance, healthcare, education, blockchain technology, and smart systems, driving unprecedented levels of efficiency, connectivity, and intelligence [29]. By leveraging cutting-edge technologies like artificial intelligence (AI), the Internet of Things (IoT), big data analytics, and robotics, Industry 4.0 is redefining how businesses operate and deliver services. In finance, for example, it enables faster, secure transactions and the rise of digital currencies, while in healthcare, it fosters personalized treatment and predictive diagnostics through data-driven insights [30]. Similarly, in education and blockchain, Industry 4.0 enhances learning experiences and ensures secure, transparent systems. Ultimately, this shift is transforming industries, promoting innovation, and opening new possibilities for economic growth and societal advancement. These innovations have become a key competitive advantage in global economies, offering more efficient ways to manage daily activities across various aspects of life [31]. In many cases, they provide the sole solution to unique challenges, such as during the COVID-19 pandemic when physical activities were largely suspended. During this time, people shifted to electronic transactions, conducted classes through e-learning platforms, engaged in commerce via e-commerce sites, and even accessed healthcare services remotely through telemedicine [32]. This shift has highlighted the necessity and critical role of these innovations in fostering human development and driving economic growth. Figure 1 illustrates the industry 4.0 technologies.

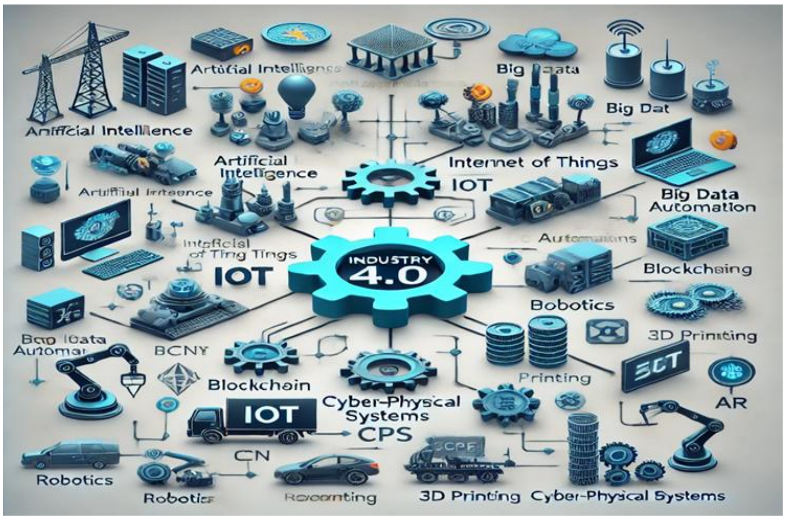

Figure 1. Industry 4.0 Technology Architecture

2.2 Applications of Industry 4.0

The following table outlines the key applications of Industry 4.0 across various sectors, highlighting the transformative role of advanced technologies such as IoT, AI, robotics, blockchain, and big data. Each application area is paired with real-life examples that demonstrate how these innovations are being implemented to drive efficiency, innovation, and growth. From manufacturing to healthcare, finance to agriculture, Industry 4.0 is reshaping industries and enabling new opportunities for digital transformation in both developed and emerging economies. Table 1 shows the applications of industry 4.0 in various areas and disciplines.

Table 1. Applications of Industry 4.0 in Real Life

Application Area	**Description**	**Real-Life Examples**
Manufacturing & Automation	Integration of smart machines, robotics, and automation systems to optimize production and enhance efficiency [27].	Tesla uses automated robots and AI-driven processes in its manufacturing plants for vehicle production. Siemens employs smart factories for flexible production.
Healthcare & Telemedicine	Use of IoT, AI, and big data to improve patient care, enable remote monitoring, and automate health services [2].	Philips HealthTech uses IoT-enabled devices for remote patient monitoring. Teladoc provides virtual healthcare services using telemedicine technologies.
Finance & Digital Payments	Blockchain, AI, and digital currencies improve transaction security, reduce costs, and enable contactless payments [33].	China's eCNY (digital yuan) is being used for government transactions. PayPal and Venmo use AI for fraud detection in digital payments.
Supply Chain & Logistics	IoT and AI-driven systems for real-time tracking, inventory management, and optimized supply chain operations [31].	Amazon uses AI and robotics for inventory management and delivery optimization. DHL employs IoT for real-time tracking and AI for logistics optimization.
Smart Cities & Infrastructure	Use of IoT, big data, and AI to create connected, efficient, and sustainable urban environments [30].	Singapore has implemented smart city technologies, including IoT-based traffic management and smart utilities. Barcelona uses sensors to monitor air quality.
E-commerce & Retail	AI, IoT, and data analytics improve personalized shopping experiences and streamline operations [34].	Amazon uses AI for personalized product recommendations and smart warehouses for faster delivery. Alibaba employs smart logistics for efficient product delivery.
Education & E-Learning	Digital platforms and tools like AI and VR enable remote learning and personalized education [35].	Coursera and edX provide online courses using AI to personalize learning. VR-based learning in institutions like Stanford University offers immersive experiences.
Agriculture & Farming	IoT, robotics, and AI enhance crop monitoring, precision farming, and food production efficiency [5].	John Deere uses AI-driven equipment for precision farming. The Climate Corporation applies IoT to monitor crop health and optimize farming practices.

Source:(Statista, 2024)

Table 1 highlights how Industry 4.0 technologies are being applied across various sectors to enhance efficiency, productivity, and innovation in real-world settings. However, this research is focused in the application of industry 4.0 in the financial sector leveraging the digital currency innovations.

2.3 Sentiment Analysis

Social media serves as an abundant pool of information for sentiment analysis, providing useful information that could enhance customer happiness, guide decisions, and deepen comprehension of public opinion [18]. Supervised and ensemble learning models are commonly used in sentiment analysis on social media to categorize sentiments into groups like positive, negative, and neutral [36]. To create and assess sentiment analysis models, techniques like XGBoost, Random Forest, Support Vector Machines (SVM), and Naïve Bayes are often utilized [21].

Existing studies utilizing SVM and XGBoost algorithms have demonstrated their effectiveness in various predictive and classification tasks, particularly in fields such as finance, healthcare, and marketing [37]. For example, studies by [38] utilizes the SVM model in analyzing the opinion of people on the use of cryptocurrencies in India. The model was found to preform relatively good in accuracy and precession. Similarly [39] explored the SVM model to predict the prices of digital currencies based on online user opinions gathered from Twitter. The findings indicated a commendable level of accuracy and precision. These results highlight the SVM model's viability as an effective algorithm for sentiment analysis in the context of digital currencies. Further studies [33] investigates the application of Support Vector Machine (SVM) for sentiment analysis in social media data pertaining to healthcare. To better capture the differences in health-related feelings, the study focusses on enhancing the performance of SVM models by combining sophisticated kernel functions and feature selection procedures. Compared to conventional SVM techniques, the enhanced SVM models exhibit greater classification accuracy and handle complex healthcare-related emotions more efficiently. The study demonstrates how these innovative techniques effectively collect insightful information from social media posts on healthcare. Additionally, [29] examined the use of SVM to sentiment analysis of customer evaluations. According to the study, data augmentation greatly improves the performance of support vector machines (SVM) models, resulting in improved generalization and accuracy when classifying customer reviews' sentiment. This method works well for managing unbalanced datasets and enhancing the general resilience of the model.

One sophisticated ensemble technique that is well-known for its effectiveness and performance is the XGBoost model [24]. It excels at managing unbalanced datasets and providing accurate sentiment categorization. Existing research by [40] examined the application of XGBoost in sentiment analysis of customer evaluations, contrasting its efficacy with alternative machine learning models such as Logistic Regression and Naïve Bayes. The study concludes that XGBoost improves unbalanced dataset handling and classification accuracy considerably. This model is a better option for consumer sentiment analysis since it can identify intricate links in the data. Seemingly, other research such as [22] appear to investigate the use of XGBoost for sentiment analysis of social media postings, emphasizing how well it processes and categorizes feelings from a variety of noisy data sources. The study shows that when it comes to sentiment categorizations for social media material, XGBoost performs with excellent efficiency and accuracy.

The gradient boosting capabilities of the model are responsible for its higher performance, as they improve its capacity to handle diverse and large datasets. Existing studies include [15], [21], [23] which utilizes the XGBOOST in detecting multilingual influences among users from an online extracted dataset. The model is found to be of good predictive power, indicating the robustness of XGBOOST model. Similarly, [18] adapted the XGBOOST model and found it to be of good predictive power. However, there remains a significant gap in research applying these algorithms to identify and predict the determinants of digital currency adoption, particularly for emerging Central Bank Digital Currencies (CBDCs) like the eNaira. Most research has not explored a hybrid approach that combines SVM's classification capabilities with XGBoost's predictive accuracy, which could provide deeper insights and more robust models for understanding adoption patterns in the context of a developing economy like Nigeria. This study aims to fill this gap by leveraging a combined XGBoost-SVM model to analyze and predict eNaira adoption.

Even though each of these models has certain advantages and disadvantages, the research existing in publication does not combine them all to determine which strategy is best for forecasting citizens' adoption of eNaira based on internet evaluations and comments. There is a shortage of extensive study that assesses and contrasts several machine learning models in the context of eNaira adoption; past research tends to focus on distinct models or facets of sentiment analysis. By using a hybrid method of supervised and ensemble learning models, including Support Vector Machine (SVM) and XGBoost, to analyze the sentiment of eNaira-related online comments and reviews, this study aims to fill this gap. This study aims to identify which model gives the most analytical and precise indications by assessing how well different models predict public opinion and adoption relationships.

3. MATERIALS AND METHOD

The architectural diagram shown in Figure 1 illustrates how the model is made up of integrated components. The dataset is first preprocessed to transform it into a format that is adequate for the examination. After processing, the data is run through a semantic analyzer to eliminate stop words and apply lemmatization. In the feature extraction stage, the processed datasets are used to obtain feature vectors. Next, the dataset is divided into subgroups for both the training set and testing set. Once the testing data is analyzed in the classification model, the training data serves to develop the model. This method categorizes the results as positive, negative, or neutral. Lastly, using these three categories, the polarity score, which represents the dataset's degree of positivity or negativity is computed [41]. These techniques are described in the following subsections.

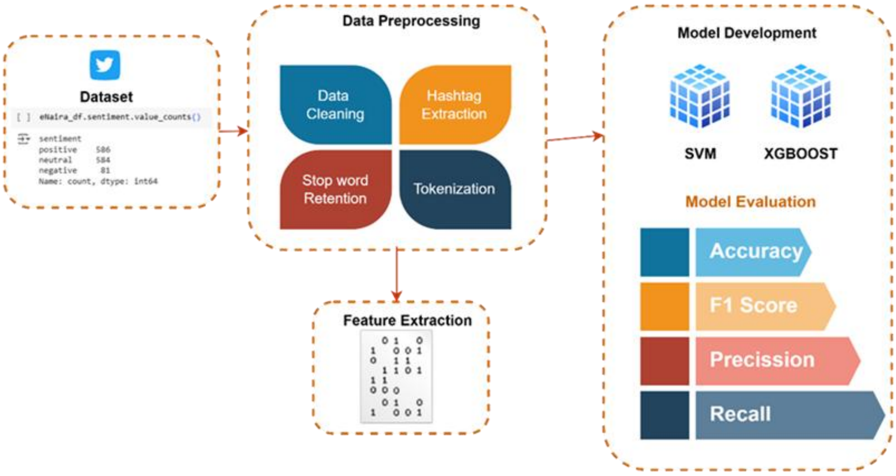

Figure 2. The Architectural Diagram of the Research

3.1 Data Collection

Data from the three main social media networks of Facebook, Instagram, and Twitter has been extracted using an online web scraper called Apify.com. This program has been used to effectively retrieve a large dataset with 1,254 items [24]. The user-generated opinions in this dataset, which includes posts, comments, and interactions, is diverse and contains a wealth of available data for the present research. The scraping process involved capturing relevant keywords such as “eNaira,” “CBDC,” “Nigerian Digital Currency,” “CBN,” “Nigerian Money,” “Financial Inclusion,” “Cashless Policy” “eWallet,” “adoption,” “Nigerian Technology,” hashtags, and all user opinions that are relevant to the study's subject, confirming that the information gathered is thorough and indicative of the general public's opinion on these platforms. Figure 3 presents the sample of the extracted raw data.

	text
0	eNaira Sensitization at the Unilag Law Ladies ...
1	eNaira continues adoption drive in Nigerian un...
2	📢 We are at Bamidele Olumilua University of Ed...
3	Barka da Sallah! May you enjoy every moment of...
4	We captured a few snapshots during our session...
...	...
1330	After months of preparation and hard work at @...
1331	New Project available 🔥 🔥 \nRegister Ice Netwo...
1332	With E-Naira, managing your finances has never...
1333	Something Big\nLoading... For everyone in our ...
1334	Scan, Pay, and Go! \n\nUse your smartphone cam...

Figure 3. Extracted Raw Data

3.2 Data Preprocessing

A critical step in preparing the collected dataset for analysis is data preprocessing [41]. It consists of many steps that are intended to ensure that the raw data is clean, transformed, and arranged in a way that makes it appropriate for sentiment analysis [42].

3.2.1 Data Cleaning

To enhance the quality of the data, data cleaning involves identifying and eliminating errors and discrepancies from the data [43]. Inadequate data cleaning procedures can result in failures, flawed analysis, dataset inaccuracies, and ultimately incompatible datasets for predictive modelling applications [8]. The procedure includes:

I. **Tokenization:** Breaking down text into individual words or tokens, which are the basic units for further analysis.
II. **Stop Words Removal:** Removing common words (e.g., "and" "the," "is") that do not carry significant meaning in the context of sentiment analysis.
III. **Stemming and Lemmatization:** Reducing words to their root forms (e.g., "running" to "run") to ensure consistency in text analysis.
IV. **Lowercasing:** Converting all text to lowercase to avoid case sensitivity issues.

3.2.2 Feature Extraction

Transforming text data into numerical representations using techniques like TF-IDF (Term Frequency-Inverse Document Frequency) or word embeddings to prepare it for machine learning models like Data Frames (DF), this step is referred to as Vectorization [24].

3.2.3 Data Balancing

This step ensures that the dataset has a balanced distribution of positive, negative, and neutral sentiments to prevent bias in model training [34].

3.2.4 Train-Test Split

This involves dividing the dataset into training and testing subsets to evaluate model performance and prevent overfitting. Figure four presents a sample of the cleaned dataset and figure five illustrates a word cloud of the dataset [6].

	text	label	clean_text
0	eNaira Sensitization at the Unilag Law Ladies ...	0	enaira sensitization unilag law ladies event
1	eNaira continues adoption drive in Nigerian un...	0	enaira continues adoption drive nigerian unive...
2	Barka da Sallah! May you enjoy every moment of...	1	barka da sallah may enjoy every moment year ei...
3	eNaira sensitization carried out at the UNILAG...	0	enaira sensitization carried unilag law ladies...
4	eNaira takes adoption drive to Nigerian univer...	0	enaira takes adoption drive nigerian universit...

Figure 4 sample of the cleaned dataset

Figure 4 shows the classification of the dataset base on positive, negative and neutral categories. Figure 5 below presents the generated word cloud of the dataset. The word cloud presents a graphical depiction of the most frequently occurring words in the dataset. This word cloud visualizes the prominence of specific terms and phrases related to eNaira, with larger words indicating higher frequency. The word cloud is a valuable tool for identifying key themes and topics that dominate the discussion, helping to uncover the main drivers behind the sentiments expressed in the dataset [44].

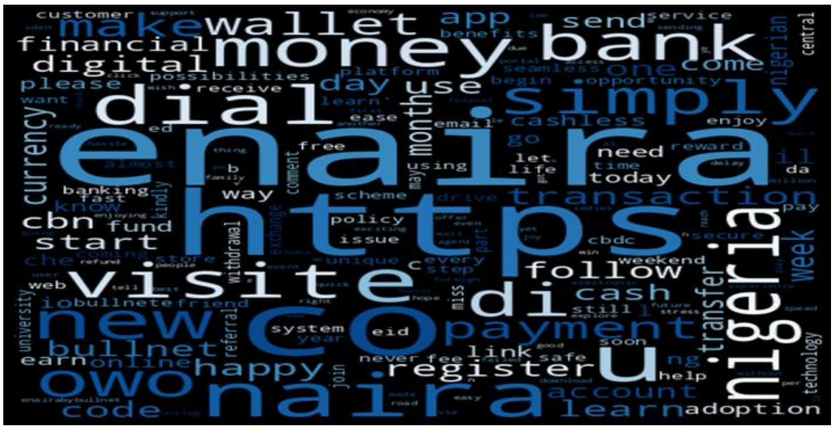

Figure 5 The word cloud of that raw dataset

4. RESULTS AND DISCUSSION

Figure 6 below illustrates the distribution of sentiments in the collected data: 67% of the data is categorized as negative, 21% as positive, and 12% as neutral. This distribution reveals that a substantial portion of the citizens expresses negative sentiments about the eNaira digital currency adoption, indicating strong public disapproval. Only 31% of the citizens convey positive sentiments about the adoption of eNaira. Meanwhile, 12% of the citizens are neutral, reflecting mixed opinions that could be either positive or negative. The negative sentiments often reflect concerns such as dissatisfaction with government policies, criticism of the eNaira wallet, worries about the security of the eNaira platform, or doubts about the project's sustainability. Positive sentiments, on the other hand, include support for the eNaira, optimism regarding its security, satisfaction with the eNaira wallet, and enthusiasm for the government's policies.

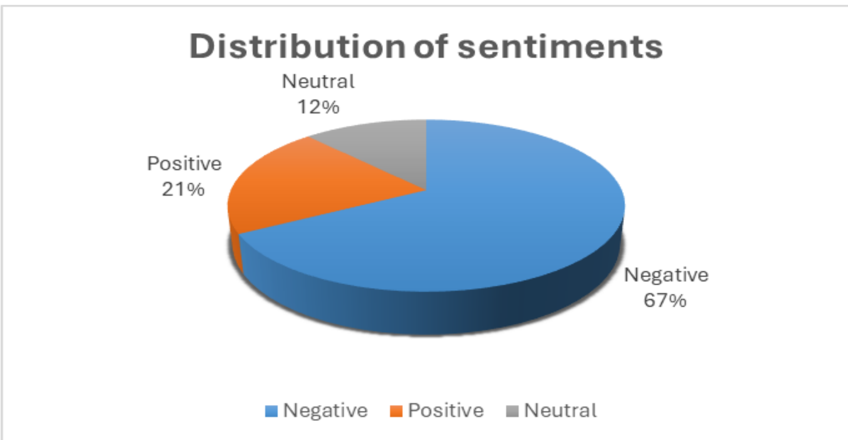

Figure 6. Classification of Datasets

To evaluate the individual performance of the algorithms used in the analysis: accuracy, precision, recall, and F1-score indicators were computed using a manually annotated dataset of 1,254 entries. An overview of these metrics is outlined below:

a. Accuracy

Calculates the ratio of correctly predicted results to all the predictions that were made. The following formula is used to determine a machine learning model's accuracy [45].

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (1)$$

b. Recall

Sometimes referred to as true positive rate or sensitivity, this metric assesses how well a machine learning model can detect positive examples [45]. The recall calculation formula is:

$$Recall = \frac{\text{TP}}{\text{TP+FN}} \quad (2)$$

c. Precision

The ratio of accurately anticipated positive cases to the total number of positive instances is computed using this measure [45]. The formula is:

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \quad (3)$$

d. F1-score

The measurement that provides a fair assessment of the two harmonic mean of recall and accuracy [46]. It is calculated as:

$$F1 - Score = \frac{2*\text{recall}*\text{precision}}{\text{recall+precision}} \quad (4)$$

In accordance with the above formulated indicators, Tables 1 and 2 display the performance metrics for SVM, and XGBoost classifiers. According to Table 1, SVM achieves 78% accuracy with precision rates of 1 % for neutral 71 % for negative, and 88% for positive sentiments. Its recall values are 11% for neutral, 92% for negative, and 76% for positive, and the F1-scores are 20% for neutral, 80% for negative and 81% for positive. In table 2, XGBoost attain a higher accuracy of 94% with precision rates of 1.00% for neutral, 85% for negative, and 77% for positive. Its recall values are 28% for neutral, 91% for negative, and 81% for positive, and the F1-scores are 20% for neutral, 81% for negative, and 80% for positive. In general, XGBoost performed accurately than SVM in all sentiment classifications. XGBoost exceed SVM in terms of precision for neutral and negative viewpoints. When it comes to neutral and positive emotions SVM is more predictive and XGBoost but XGBoost gets the best recall for negative sentiments. Overall, XGBoost produce greater F1 scores than SVM especially for neutral and positive feelings. The corresponding analytical findings are detailed in Tables 2 and 3 below, and Figure 6 displays a visual performance chart for the specified machine learning models.

Table 2 SVM Classification Report

Label	Precision	Recall	F1-Score	Support
0	0.71	0.92	0.80	106
1	0.88	0.76	0.81	120
2	1.00	0.11	0.20	18
Accuracy			0.78	
macro avg	0.86	0.60	0.61	244
weighted avg	0.86	0.78	0.76	244

Table 2 presents the evaluation result of the SVM model indicating accuracy, precision and recall.

Table 3 XGBoost Classification Report

Label	Precision	Recall	F1-Score	Support
0	0.77	0.91	0.83	106
1	0.85	0.81	0.83	120
2	1.00	0.28	0.43	18
Accuracy			0.94	
macro avg	0.87	0.66	0.70	244
weighted avg	0.83	0.81	0.88	244

Table 3 presents the evaluation result of the SVM model indicating accuracy, precision and recall.

Tables 2 and 3 show the accuracy of the two models in predicting the adoption rate of the eNaira digital currency among citizens. The results indicate that the XGBOOST model outperformed the SVM model, achieving an accuracy of 94% compared to the SVM model's 78%. Figure 7 illustrates the performance metrics of both models, including precision, recall, and F1-score.

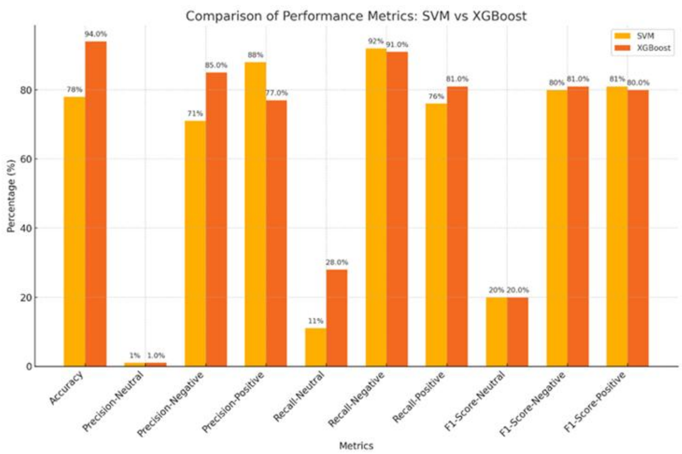

Figure 7. Model Performance Metrics

The chart above compares the performance metrics of SVM and XGBoost in analyzing sentiment data across accuracy, precision, recall, and F1-score. XGBoost, represented in the dark color, demonstrates notably higher accuracy at 94%, compared to SVM's 78%. Precision, recall, and F1-scores across sentiment categories (neutral, negative, positive) further highlight XGBoost's consistent superiority, particularly in managing negative and positive sentiments, where it achieves higher precision and recall. The SVM model, represented in blue, performs moderately well, especially in negative sentiment detection but is outperformed by XGBoost across most metrics. This comparison indicates that XGBoost's ensemble capabilities allow it to better capture and analyze nuanced sentiment distinctions, making it a more effective model for sentiment analysis in this dataset.

5. CONCLUSION

This research highlights the impact of Industry 4.0's revolution on the financial sector by exploring the adoption of digital currency as a subset of Industry 4.0, using Nigeria's eNaira digital currency as a case study. Machine learning models were leveraged to determine the adoption rate of the eNaira among Nigerian citizens. The findings demonstrate that applying machine learning techniques significantly improves predictive modeling and enables the identification of sentiment trends on social media, particularly concerning the adoption of emerging technologies like the eNaira within specific demographics or contexts. By leveraging these techniques, the study has successfully extracted and analyzed public opinions, categorizing sentiments toward eNaira as positive, negative, or neutral. Furthermore, the study has highlighted key factors that either influence or impede the adoption of eNaira digital currency among citizens, such as issues related to poor internet access, insufficient governmental support, and concerns over the security of the eNaira platform. These insights, derived from the raw data, are guidelines for policymakers as they seek to address the barriers to the low adoption of the novel eNaira digital currency. The research findings reveal that while SVM machine learning model demonstrated reasonable accuracy rates of 78%, it is outperformed by the XGBoost algorithm, which achieved higher accuracy rates of 94%. This superior performance of the XGBoost models in this study suggests their suitability for future sentiment analysis projects in similar contexts. hence, the XGBoost model is recommended for further sentiments analysis due to its effectiveness in accurately analyzing and predicting public sentiment, thereby providing robust insights that can guide decision-making processes in technology adoption across developing countries.

6. LIMITATIONS AND DIRECTION FOR FUTURE STUDIES

Given the novelty of the eNaira digital currency, obtaining sufficient data for analysis has been challenging. While Twitter is often a preferred platform for gathering data for sentiment analysis, this research collected data from three of the most popular social media platforms: Facebook, Twitter, and Instagram, resulting in a dataset of only 1,254 entries. It is recommended that further research be conducted and published using a more substantial and readily available dataset on eNaira to improve the accuracy and reliability of future studies. The superior performance of the XGBoost model, as observed in this study, is limited to the dataset that was available for analysis. Further research is advised with a more extensive dataset to thoroughly evaluate the performance of the SVM and XGBoost models. Most of the raw data obtained reflect individual perspectives on the adoption of the eNaira. It is recommended that future studies focus on the organizational perspectives regarding the adoption of the eNaira digital currency. The findings of this research have identified key factors hindering the adoption of the eNaira among citizens. It is recommended that policymakers address these factors to enhance the adoption of the eNaira among the populace.

7. REFERENCES

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