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Deep Neural Network Model for Evaluating and Achieving the Sustainable Development Goal 16

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Abstract: The decision-making process for attaining Sustainable Development Goals (SDGs) can be enhanced through the use of predictive modelling. The application of predictive tools like deep neural networks (DNN) empowers stakeholders with quality information and promotes open data policy for curbing corruption. The anti-corruption drive is a cardinal component of SDG 16 which is aimed at strengthening state institutions and promoting social justice for the attainment of all 17 SDGs. This study examined the implementation of the SDGs in Nigeria and modelled the 2017 national corruption survey data using a DNN. We experimentally tested the efficacy of DNN optimizers using a standard image dataset from the Modified National Institute of Standards and Technology (MNIST). The outcomes validated our claims that predictive analytics could enhance decision-making through high-level accuracies as posted by the optimizers: Adam 98.2%; Adadelta 98.4%; SGD 94.9%; RMSProp 98.1%; Adagrad 98.1%.

Keywords: sustainable development goals; predictive modelling; SDG 16; corruption; deep neural network

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1. Introduction

Deep learning is a predictive model and a machine learning component. It uses algorithms and data to make classifications, predictions, and decisions. Explicit programming is not involved in deep learning [1] Predictive models like deep learning facilitate decision-making in sustainable development domains by eliciting knowledge from raw data hierarchically, using algorithms rather than leveraging the domain experts' outlined features. This is accomplished through many layers of non-linear processing units to make predictions or take actions that are in line with the defined target objective.

Generally, a neural network is categorized as a deep model when it has more than one hidden layer. Apart from deep neural networks (DNNs), architectures like deep random forests [2], neural processes [3], and deep Gaussian processes [4] have multiple layers and these are also classified as deep learning models.

Applying a predictive tool like deep learning to a national database such as the Nigerian national corruption survey database would help to detect hidden and useful patterns for understanding the corruption disposition behaviors of the citizenry. The unbiased information that is generated could be used to guide decisions that are bordering on designing value re-orientation programmes. Such value re-orientation aims to instill the core values of accountability, transparency, and probity in leaders and are important in attaining the Sustainable Development Goals (SDGs). Corruption corrodes away at the public resources, weakens institutions, promotes political instability, and makes the attainment of sustainable development impossible [5].

The presence of corruption in a country means the erosion of peace, justice, strong institutions, and partnerships, which are the ideals of SDG 16 [5,6]. Essentially, the attainment of this goal (SDG 16) is fundamental to the achievement of the remaining SDGs [7,8]. This implies that an effective and efficient evaluation framework for national development, such as Nigeria's Economic Recovery and Growth Plan (ERGP) [9] should place a high premium on an anti-corruption drive. The ERGP is aimed at attaining all the SDGs by 2030 [10]. Hence, detecting patterns in national corruption databases for gauging the disposition of citizens to conduct corrupt practices for the purpose of taking correctional measures is germane.

This study modeled the 2017 Nigerian national corruption survey dataset [11] using a DNN to understand the underlying corruption patterns. In developing economies like Nigeria, data are not readily available. Hence, the study has used only this dataset. Also, to underscore the strategic role of image data (e.g., biometrics) in the anti-corruption effort, a series of experiments were performed using standardized image data from the Modified National Institute of Standards and Technology (MNIST). Corruption in Nigeria is endemic [12,13] and this threatens the actualization of the national economic plan (ERGP) as well as the SDG implementation plans [7,9]. A DNN is used as the predictive model for extracting information from the dataset. Bamberger (2016) observed that the inadequate use of data analytics impacted adversely on the actualization of previous global sustainable development agendas.

The research question is: how useful is predictive modeling in the formulation of policies, the implementation of programs, and the management of projects for the purpose of curbing corruption in a bid to achieve the SDGs?

The objectives of this work are:

1. To evaluate the impact of corruption on sustainable development policies, programs, and projects.
2. To model corruption-related data with a view to understanding patterns for the improved anti-corruption drive.
3. To experimentally demonstrate the efficacy of deep neural networks as a predictive analytics tool.

In a nutshell, our study links corruption to the inability of countries to attain the sustainable development goals. To promote accountability, transparency, and probity, we advocate using a predictive model to detect patterns in datasets and take appropriate anti-corruption measures. We explain that anti-corruption efforts promote peace, justice, and strong institutions (SDG 16), forming the bedrock for achieving the remaining SDGs [14].

There is evidence of the application of machine learning in other aspects of the SDGs. For example, in making cities and human settlements resilient and sustainable, as is documented in SDG 11, the role of infrastructure such as transportation infrastructure cannot be overemphasized, as stated in SDG 9. Also, SDG 17 specifies that trade is one of the means of implementing and revitalizing global partnerships to enhance sustainable development. The role of transportation in trade is critical, and machine learning has been used to boost transportation and logistics strategies [15,16]. To improve image categorization performance, DNNs are potent [17]. This is relevant for enhancing image datasets such as the standardized image data from MNIST that we used in this current research.

The paper is organized as follows: Section 2 focuses on the related works, while Section 3 outlines the methodology. Section 4 is an explanation of the series of experiments that we performed and the results that we obtained. In Section 5, we explain how predictive modelling is useful for evaluating the SDGs. Section 6 is a discussion of how we achieved the objectives of the study. Finally, Section 7 contains the conclusion and future work.

2. Related Works

2.1. Deep Learning as a Predictive Model

Deep learning as a predictive tool has gained popularity in recent years [1]. There are many deep learning models, such as deep random forests [2], neural processes [3], and deep Gaussian processes [4]. However, the DNN remains a force to reckoned with among the lot. The execution of the Millennium Development Goals (MDGs) has suffered setbacks partly because of a lack of data and technology to detect the existing data patterns of their strategic interventions [18]. To avoid the SDGs suffering the same fate, data collection efforts are being intensified at international, national, and sub-national levels. In particular, the Federal Bureaus of Statistics of various countries are stepping up their efforts to ensure that the national data are well articulated to support the national plans and the domestic actualization of the SDGs. Applying data analytics technologies to big data makes greater sense than not doing so as the patterns in the data can be detected with them, which aid the timely and reliable decision-making, particularly during emergencies.

In recent years there has been a drastic increase in using ICT-based appliances like smartphones, tablets, and sensors, and these devices are generating a lot of data. In the past, it was difficult to trace the new patterns and relationship in data; now it becomes possible to present data in a simple way which are understandable to everybody [19–22].

In the last few years, the number of applications of big data for evaluating the SDGs in subject areas such as gender-responsive evaluations and equity-focused evaluations [1] are increasing. For example, the Data2X collaboration illustrates the use of big data and new applications in the SDG evaluation to fast-track their attainment. Furthermore, it offers potential applications for equity-driven (SDG 10) and gender-sensitive (SDG 5) reviews. Presently, the vast majority of these technological applications have been utilized for research and design instead of directly for program evaluation. In any case, a number of techniques could be adapted for programme evaluation. In our current study, we explore the use of neural network-based applications for detecting patterns in corruption data. Our aim is to show how actors (SDG execution) can leverage such patterns which have been learned to enhance the anti-corruption research, program design, and evaluation as a cardinal component of SDG 16. The DNN is a foremost deep learning technique and a predictive model [1].

2.2. Sustainable Development Goals

We measured the SDGs in terms of their pillars, indicators, goals, and targets. Our findings are summarized in the SDGs measurement pyramid in Figure 1, below.

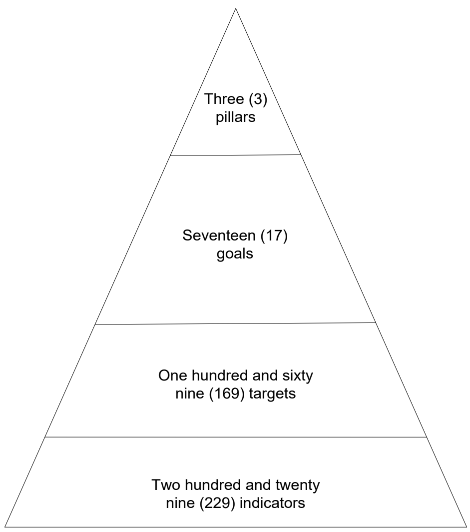

Figure 1. SDG measurement pyramid.

There are three pillars that include social, economic, and environmental pillars [23]. The number of goals is 17, the total number of targets is 169, and the number of indicators is 229 [1]. It is expected that various countries' national sustainable development plans would be evaluated in the context of the SDGs' benchmark indicators and targets. In Nigeria, the current national sustainable development plan is the ERGP [9,24]. Though many risks threaten the implementation of sustainable development programs in Nigeria, such as insecurity, poor infrastructure, corruption, and an unfavorable macroeconomic environment, corruption remains a principal factor [13,25]. Corruption threatens peace, social justice, and strong institutions, which makes the attainment of SDG 16 unrealistic. In the absence of peace, justice, and strong institutions, the macroeconomic environment cannot support the actualization of the remaining 16 SDGs [5].

2.3. Corruption and the Sustainable Development Goals

Corruption weakens the macroeconomic environment and makes it difficult for a country to have favorable socio-economic indicators. All of these factors culminate in the inability to attain the SDGs. Since the implementation of the SDGs is evaluated on a national and sub-national basis, we examined the implementation of various sustainable development policies, programs, and projects in Nigeria. These initiatives are coordinated under its Economic Recovery and Growth Plan (2017–2020) and the recent Nigeria Economic Sustainability Plan, occasioned by the COVID-19 pandemic [26,27]. The various initiatives are targeted at keeping the country on the sustainable development path in the face of threats like insecurity (insurgency), climate change, and the COVID-19 pandemic [28]. However, as outlined in [11], public officials' corrupt practices can adversely impact achieving the SDG targets. Table 1 shows the evaluations of selected programs and its corresponding SDGs [29].

Table 1. Qualitative assessment of SDG implementation in Nigeria.

SDG	SDG Targets	Nigerian Initiatives	Adverse Impact of Corruption
Goal 1. End poverty in all its forms everywhere	By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than $1.25 a day	1. Social investment programme such as conditional cash transfer. 2. Special Public Works Programme for creating 774,000 jobs.	Public resources stolen by government officials make resources limited to reach all the poor and vulnerable
Goal 2. End hunger, achieve food security and improved nutrition and promote sustainable agriculture	By 2030, end hunger and ensure access by all people, in particular the poor and people in vulnerable situations, including infants, to safe, nutritious and sufficient food all year round	Anchor borrower programme that make soft loans available to farmers with single digit interest and with little or no collateral.	Some individuals who are not farmers disguise themselves as farmers to collect the loans for other purposes.
Goal 3. Ensure healthy lives and promote well-being for all at all ages	By 2030, reduce the global maternal mortality ratio to less than 70 per 100,000 live births	Primary healthcare facilities being built in rural areas	Stealing of healthcare facilities provided by government.
Goal 4. Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all	By 2030, ensure that all girls and boys complete free, equitable, and quality primary and secondary education leading to relevant and effective learning outcomes	The home-grown school feeding programme and free education programme to encourage massive enrolment in schools.	Government officials divert resources for personal use. Food vendors offer low quality meals to maximize profit.
Goal 5. Achieve gender equality and empower all women and girls	End all forms of discrimination against all women and girls everywhere	A massive campaign against female genital mutilation (FMG)	Some individuals still secretly support FMG, putting personal interest above national/collective interest.
Goal 6. Ensure availability and sustainable management of water and sanitation for all	By 2030, achieve access to adequate and equitable sanitation and hygiene for all and end open defecation, paying special attention to the needs of women and girls and those in vulnerable situations	The building of dams and integrated water schemes.	Public utility officials divert money meant for water facility maintenance.

Transparency International has quantitatively measured the levels of corruption in Nigeria in terms of the SDG 16 targets, using the strength of its legal and institutional frameworks to produce an anti-corruption response in 17 policy areas [5]. The global anti-graft body also noted that Nigeria had lost about 400b dollars to corruption since attaining independence in 1960. However, since 2015, Nigeria's anti-graft efforts have been intensified, culminating in a new anti-corruption strategy in 2017. The implementation of anti-corruption policies like Integrated Payroll and Personnel Information Systems

(IPPIS), Treasury Single Account (TSA), and Biometric Verification Number (BVN) have been vigorously pursued. Critical legislation is also being formulated on whistleblowing, money laundering, illicit financial flows, and asset recovery. Through the Code of Conduct Tribunal, politically exposed persons are being compelled to declare their assets accurately. The armed forces and law enforcement agencies' operations are being opened up to mitigate corruption and embezzlement, which impair the fight against terrorism and organized crime. There is a need to improve access to information and encourage an open data policy. Greater transparency is also required in public procurement and beneficial ownership. Anti-corruption agencies like the Independent Corrupt Practices Commission (ICPC), and the Economic and Financial Crimes Commission (EFCC) [11] should operate in an environment that is devoid of political interference. If it were not for the policy areas that are outlined in [5] being addressed, the SDG 16 targets would not be met in Nigeria.

Since SDG 16 provides the platform for actualizing the other SDGs, it follows that it would be challenging to attain the other goals if corruption is not tackled.

2.4. Literature Review

The past works on the predictive model (deep neural networks), sustainable development goals, and corruption are as follows.

Dabura [4] postulated that the generic gradient descent optimization algorithm's objective when applied to neural network problems, is finding optimal parameter values that reduce the error between predicted and actual values using initial parameter values. In other words, the optimization algorithm called gradient descent searches for optimal weights that reduce prediction error. The steps for gradient-based optimization include initializing the weights with random values and calculating error; computing the gradient which ensures the change in the values of weights is in the direction in which error is minimized; updating weights using gradients; using new weights for prediction and for computing error; and repeating gradient computation and weight updating until adjustment to weights doesn't appreciably reduce the error. The work offers insight into stochastic optimization algorithms' workings, particularly as applicable in artificial neural networks and deep learning. However, it is silent on applying DNN as a prediction tool for detecting patterns in sustainable development data such as corruption survey data. Our present study applies the predictive model to corruption survey data intending to elicit useful patterns for improved anti-graft measures. This is in a bid to facilitate the implementation of the SDGs.

Brownlee [1] opined that neural network is useful for solving a wide range of problems. As long as data and problems exist in any field of human endeavor, machine learning can be applied. DNN apart, other deep learning tools useful for predictive modeling include deep random forests, neural processes, and deep Gaussian processes. The study revealed that DNN remains a force to reckon with among the lots. The author emphasized that in recent years, deep learning as a predictive tool has gained popularity because of its ability to handle complex problems. Our present study considered that tackling the impact of corruption on the attainment of sustainable development goals is a hydra-headed problem that a sophisticated predictive tool like DNN should be applied to resolve.

In [26], the authors proposed a compendium of the statistical information needed for monitoring and evaluating progress in SDGs implementation in Nigeria. It emphasizes the essence of timely, disaggregated, reliable, and accessible data for measuring progress, informed decision-making, and ensuring that no one is left behind. Apart from attaining the SDGs targets, the government needed to be provided with reliable, adequate, and timely statistical information to implement its national plan christened Economic Recovery and Growth Plan (ERGP). The compendium is comprehensive and robust statistical information that takes into cognizance Nigeria's peculiarity. It is a product of the combined data collection efforts of several agencies. Despite emphasizing the significance of data in achieving the SDGs, the work does not show the link between corruption and the attainment of SDGs. This current study establishes a relationship between corruption and the attainment of

SDGs. We also add value to existing data by applying data analytics (predictive modeling) to determine knowledge engineering for informed decision-making.

Ugaz [5] dwells on measuring progress towards attaining SDG 16, which focuses on strong institutions, peace, and justice. Among others, Goal 16 contains obligations to tackle corruption, scale up transparency, fight illegal financial flows and improve information access. The author emphasizes that Transparency International believes that achieving the other goals is nearly impossible in the absence of significant action to mitigate corruption. Sustainable development in the face of corruption is a mirage since it endangers economic growth, raises poverty levels, and deprives vulnerable groups of equal access to critical social services like healthcare, education, water, and sanitation. Transparency International also observed that the menace is not an exclusive preserve of developing countries, urging developed countries to expedite tax evasion, external bribery, cross-border corruption, and connected illegal flow of finance, which denies less developed countries of huge sums of money on a yearly basis. Governments need to be accountable and identify strategic anti-corruption actions. The work also envisages that at international, national, and sub-national levels, there would be policy discussion and reforms aimed at reducing corruption in order that none is kept behind in the implementation of the SDGs. Despite the categorical stance of the work on the negative impact of corruption on achieving the SDGs, it does not stress how corruption data could be harnessed using predictive models for effective and efficient anti-graft measures.

3. Methodology

We studied the 2017 national corruption survey data of Nigeria with a view to understanding the variables and recognizing the corruption patterns that slow the development in the country. Other datasets could have been considered to broaden our basis for a generalization, but the dearth of data in developing economies like Nigeria removed this possibility. In any case, we considered that the 2017 data were reasonable enough for drawing meaningful conclusions. To further aid the understanding of the patterns, we modeled the dataset using deep neural networks. Based on our realization that image data plays a critical role in stopping unwholesome practices in the implementation of policies, programs, and projects, we experimentally validated the potential of DNN optimizers for accurate predictions. For our series of experiments, we used Python deep learning tools like the Keras application interface and the standardized handwritten image dataset from the Modified National Institute of Standards and Technology (MNIST).

Data Exploration and Coding

The variables that are modeled in this study were obtained from Nigeria's 2017 national corruption survey data [11]. In general, they reflect how the backgrounds of the respondents impact the corruption perception. The variables also reflect the degree of torruption involvement of officials in various institutions in Nigeria. More detailed explanations of the variables are outlined in Table 2. A manual pre-processing method was used to improve (cleanclean up data.

Table 2. Variables and meanings.

ID	Feature	Meaning
X_1	State	State of origin of respondent
X_2	Zone	Geo-political zone of respondent
X_3	Population	Population estimate of state in 2016
X_4	Urban	Percent of state that is urban
X_5	Rural	Percent of state that is rural
X_6	Contact rate	The rate at which bribe-givers make contact with bribe-takers

Table 2. *Cont.*

ID	Feature	Meaning
X_7	Prevalence of bribery	The rate of bribery incidences
X_8	Police officers	Prevalence of bribery among police officers
X_9	Car registration/driving license officers	Prevalence of bribery among car registration/driving license officers
X_{10}	Public utilities officers	Prevalence of bribery among public utilities officers
X_{11}.	Tax/revenue officers	Prevalence of bribery among tax/revenue officers
X_{12}	Teachers/Lecturers	Prevalence of bribery among teachers/lecturers
X_{13}	Member of the Armed Forces	Prevalence of bribery among members of the armed forces
X_{14}	Officials from Traffic Management Authority	Prevalence of bribery among officials from Traffic Management Authority
X_{15}	Judges/Magistrates at the court	Prevalence of bribery among judges/magistrates at the court
X_{16}	Immigration Service officers	Prevalence of bribery among Immigration Service officers
X_{17}.	Doctors/Nurses	Prevalence of bribery among doctors/nurses
X_{18}	Elected representatives from Local/State	Prevalence of bribery among elected representatives from local/state regions
X_{19}	Judges/Magistrates at the court/Prosecutors	Prevalence of bribery among judges/magistrates at the court/prosecutors
X_{20}	Embassy/consulate officers of foreign countries	Prevalence of bribery among embassy/consulate officers of foreign countries
X_{21}	Customs officers	Prevalence of bribery among customs officers
X_{22}	Other public official/civil servant	Prevalence of bribery among teachers/lecturers
X_{23}	Bribe payers	Frequency of bribery among bribe payers
X_{24}	Per adult	Frequency of bribery per adult
X_{25}	Share of bribes paid cash	Percent of bribes paid in cash
X_{26}	Average amount of cash bribes	Mean of bribes given in cash
X_{27}	Bribery reporting rate	The rate at which corruption cases are reported
X_{28}	Pointless, nobody would care	One of the reasons why the bribery case was not reported
X_{29}	Common practice	One of the reasons why the bribery case was not reported
X_{30}	Sign of gratitude or benefit received from the bribe	One of the reasons why the bribery case was not reported
X_{31}	Fear of reprisals	One of the reasons why the bribery case was not reported
X_{32}	All other reasons	One of the reasons why the bribery case was not reported
X_{33}	Do not know to whom to report to	One of the reasons why the bribery case was not reported
X_{34}	Do not want to incur additional expenses	One of the reasons why the bribery case was not reported
X_{35}	Supervisor to the official	One of the institutions considered as most important for future reporting by respondent
X_{36}	Traditional/Village leader	One of the institutions considered as most important for future reporting by respondent
X_{37}	Police	One of the institutions considered as most important for future reporting by respondent
X_{38}	I would not report it	One of the institutions considered as most important for future reporting by respondent
X_{39}	Others	One of the institutions considered as most important for future reporting by respondent

Table 2. *Cont.*

ID	Feature	Meaning
X_{40}	Anti-corruption agencies	Agencies in Nigeria charged with the responsibility of curbing corruption
X_{41}	Journalist/media	The role of the media in anti-graft efforts in Nigeria
X_{42}	Unemployment	A prominent issue impacting Nigeria is unemployment
X_{43}	High cost of living	A prominent issue impacting Nigeria is high cost of living
X_{44}	Corruption	A prominent issue impacting Nigeria is corruption
X_{45}	Infrastructure (transport, etc. . . .)	A prominent issue impacting Nigeria is infrastructure
X_{46}	Health care	A prominent issue impacting Nigeria is health care
X_{47}	Crime and insecurity	A prominent issue impacting Nigeria is crime and insecurity
X_{48}	Ethnic or communal conflict	A prominent issue impacting Nigeria is ethnic/communal conflict
X_{49}	Housing	A prominent issue impacting Nigeria is housing
X_{50}	Political instability	A prominent issue impacting Nigeria is political instability
X_{51}	Increased	Perception of corruption trend
X_{52}	Stable	Perception of corruption trend
X_{53}	Decreased	Perception of corruption trend
X_{54}	NPF	Perception of effectiveness of anti-corruption institution such as NPF (Nigerian Police Force)
X_{55}	EFCC	Perception of effectiveness of anti-corruption institution such as EFCC (Economic and Financial Crimes Commission)
X_{56}	FHC	Perception of effectiveness of anti-corruption institution such as FHC ( )
X_{57}	FMoJ	Perception of effectiveness of anti-corruption institution such as FMoJ (Federal Ministry of Justice)
X_{58}	ICPC	Perception of effectiveness of anti-corruption institution such as ICPC ( )
X_{59}	HC (FCT	Perception of effectiveness of anti-corruption institution such as HC FCT ( )
X_{60}	PCC	Perception of effectiveness of anti-corruption institution such as PCC ( )
X_{61}	CCT	Perception of effectiveness of anti-corruption institution such as CCT ( )
X_{62}	NPF	Awareness of anti-corruption institution such as NPF (Nigerian Police Force)
X_{63}	EFCC	Awareness of anti-corruption institution such as EFCC (Economic and Financial Crimes Commission)
X_{64}	FHC	Awareness of anti-corruption institution such as FHC (Nigerian Police Force)
X_{65}	FMoJ	Awareness of anti-corruption institution such as NPF (Nigerian Police Force)
X_{66}	ICPC	Awareness of anti-corruption institution such as ICPC (Independent Corrupt Practice Commission)
X_{67}	CCT	Awareness of anti-corruption institution such as CCT ( )
X_{68}	PCC	Awareness of anti-corruption institution such as PCC ( )
X_{69}	HC FCT	Awareness of anti-corruption institution such as HC FCT ( )

The 'ID' column in Table 2 indicates that we studied 69 variables (x_1 to x_{69}). The 'Feature' column expatiates on the variables while the 'Meaning' column has a detailed description of each of the variables. The data are secondary data that were obtained from documents of the Nigerian National Bureau of Statistics which is in Nigeria's 2017 national corruption survey data [11].

We used the variables in Table 2, above, to gain insight into Nigerians' corruption disposition with a view to explaining how these behaviors can impact the implementation of the nation's economic plans such as the ERGP and the NESP, and attainment of the global SDGs. According to [30] the cost of project execution in the country is the highest globally, and procurement experts have identified corruption and the appointment of incompetent professionals in sensitive positions as key factors. The variables X_7, X_8, ... , X_{22}, for example, measure the rate of involvement of public officials in bribery and corruption in Nigeria. Corruption affects the implementation of tangible and non-tangible sustainable development initiatives: tangibles are elements such as the building of schools, drilling of water boreholes, and maintenance of health clinics; intangibles are elements such as the mobilization and sensitization campaigns on various national sustainable development efforts by the National Orientation Agency (NOA).

To fit into the DNN model, we linearly structured the data. We partitioned the 69 variables into input data and label data. The variable "Reasons for not reporting bribery case" serves as a label or supervisor (y) while the remaining 68 variables (x1, x2, ... , x68) make up the input data. The label (y) contains categorical values 1, 2, 3, ... , and 7 representing, respectively, the seven (7) reasons why Nigerians do not report bribery cases. Also, the survey report shows that the population of Nigeria was 186,435,032 people at the time of the survey. Even though a sample of the population was used for the survey, the study concluded that the patterns are reflective of the corrupt disposition of the entire population. Hence, we formulate the NCS database's dimension as containing 186,435,032 rows and 69 columns (186,435,032 $\times$ 69).

The deep learning operations in deep neural networks involve the training stage, testing stage, and working stage [1]. To train and test the deep neural network model using the NCS database, we further partitioned the dataset into testing data and training data as needed. While the training data contained 1,700,000 records, the testing data were made up of the remaining 16,435,032 records. The labels (y1, y2) of the training data and testing data contained 1,700,000 and 16,435,032 records, in that order.

The DNN as a symbolic representation of the corruption data via architectural modeling is shown in Figure 2, below.

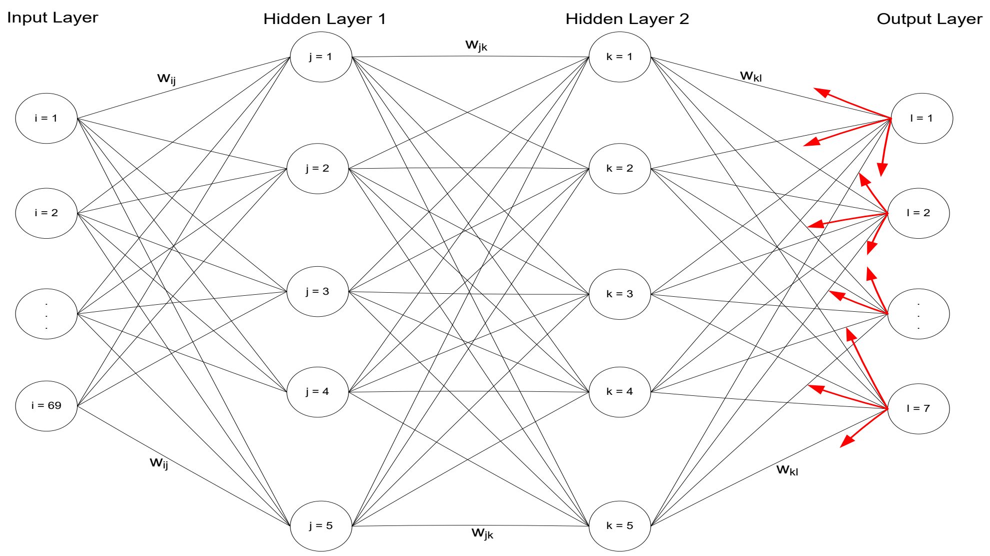

Figure 2. Forward pass and backward pass using the National Corruption Survey data.

Largely, DNN training operations are mathematical operations that are executed in computational nodes in a bid to understand the patterns that are inherent in the data (Pandey, 2018). Forward pass and backward pass make up the training operations.

4. Implementation and Results

Our conviction that a predictive model such as a DNN could be relevant to SDG implementation actors is based on its capacity to detect existing data patterns. We proved this by using the outcome of a series of deep learning experiments that we performed. Though the study explored and modeled Nigeria's national corruption survey data, the available data are small. Secondly, the dataset is not yet standardized for a sophisticated machine-learning operation. Hence, we used a proven, pre-processed, standardized and large-scale dataset known as the Modified National Institute of Standards and Technology (MNIST) for the experiments. MNIST is a database of handwritten, digital images [31]. The sustainable development data encompass text, audio, and images [18]. The choice of using MNIST is therefore apt. We experimented with five of the existing stochastic gradient descent algorithms (optimizers) that were used for training the DNN. They included SGD, Adadelta, Adagrad, RMSprop, and Adam, and the experiment platform that was used was the Python deep learning libraries [32]. The deep learning libraries that were used were the Keras application programming interface and Tensorflow. We used the Convolutional Neural Network as our DNN model since the experiment involved image processing [33]. Though the experimental outcomes included training time, loss, and accuracy, our major concern was the accuracy in the confidence that decision-makers can have when using a DNN to enhance the decision-making process.

The mean accuracies that were obtained from the series of experiments for SGD, Adagrad, Adadelta, RMSProp, and Adam are presented as percentages in Figure 3, below, for decision-makers to better appreciate the high-level prediction accuracy of the deep learning algorithms that we experimented with with.

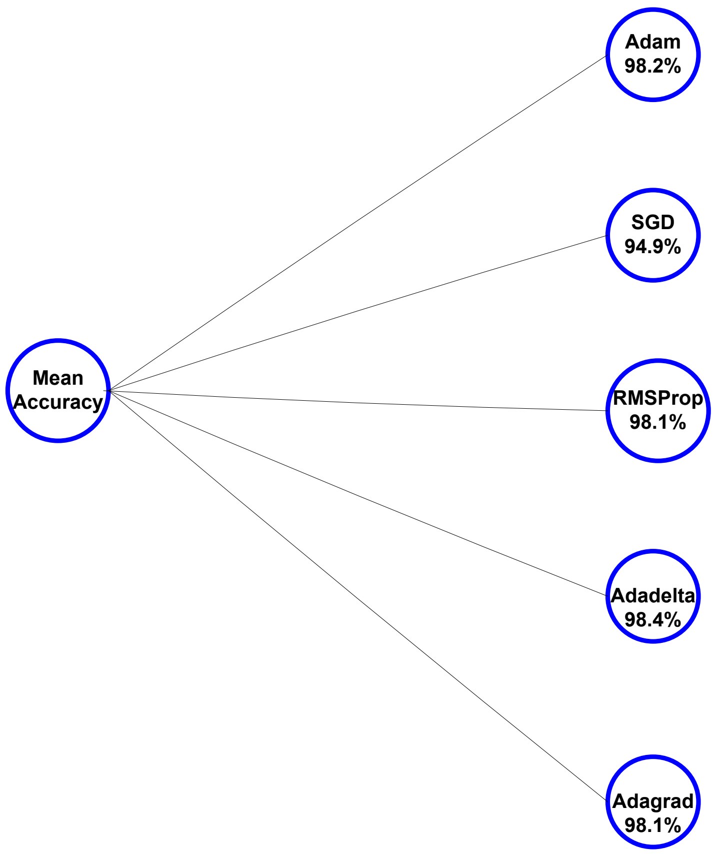

Figure 3. The mean accuracies of the various optimizers.

The series of experiments were conducted using Python deep learning libraries (Keras and Tensorflow). The essence of calculating mean accuracy for each stochastic optimizer was to have a representative figure for the ten (10) iterations that we performed. Hence, the mean accuracy is a summary of the performance of each of the deep learning algorithms in the series of experiments that were conducted.

Table 3 shows the results from another set of experiments aimed at investigating the stochastic nature of deep learning algorithms.

Table 3. Experimental results.

	Experiment 1	**Experiment 2**
Optimizer	Adam	Adam
Training dataset images	60,000	60,000
Dimension of training data	(60,000, 28, 28, 1)	(60,000, 28, 28, 1)
Testing dataset images	10,000	10,000
Mean accuracy	98.2%	98.3%
Iterations	10	10

As shown in Table 3, experiments 1 and 2 were performed to test the efficacy of the Adam optimizer using Python deep learning libraries with the same number of images as were in the training data set. However, after ten iterations, the mean accuracy of Adam in experiment 1 was 98.2%, while its mean accuracy in experiment 2 was 98.3%.

Interpretation of Results

As is typical of a predictive modelling experiment, the outcomes were measured using three parameters (loss function, training time, and accuracy). Training time measures the time it takes the predictive model to train on the presented dataset and learn a sufficient number of patterns. The difference between the predicted value and the actual output is measured by the loss function. Accuracy indicates the preciseness of a prediction, which is largely presented as a percentage. Nonetheless, we considered that prediction accuracy is of the most significance to the implementation of actors in sustainable development. Thus, we interpret the results of the experiments along this line. This underscores why we have shown the mean accuracies in Figure 3, above.

From Table 3, above, Adam's mean accuracy is 98.2%. Using the same dataset from MNIST, Adagrad posted a mean accuracy of 98.1%. The mean accuracy of Adadelta is 98.4%. RMSProp and SGD posted 98.1%, and 94.9% mean accuracies, in that order. The least mean accuracy is 94.9% (which was posted by SGD), which is a good result when decision-making with accuracy is the priority. We conclude from the results that a DNN as a predictive model can empower the implementation of actors on sustainable development with accurate forecasts for informed decision-making. This will ensure efficiency and effectiveness in taking preventive and pre-emptive measures to deal with economic emergencies, humanitarian emergencies, financial emergencies, and environmental emergencies.

A series of experiments that were performed with all the DNN optimizers (Adagrad, Adadelta, RMSProp, SGD, and Adam) show that they all exhibit stochastic behaviors. The results from the experiments, as shown in Table 2, above, practically confirmed the stochastic nature of the DNN optimizers for the same set of data and the same number of iterations; a stochastic algorithm can give different results. This is unlike deterministic algorithms that would give the same results in the same circumstances. This stochastic nature is attributable to the DNN's random choice of parameters (weights) each time that it is applied for the completion of prediction tasks [1].

5. Implications of Predictive Modelling for Evaluation of SDGs in Nigeria

Good decisions emanate from good data. However, data have to be processed to elicit timely, unbiased, and reliable information that is used in the decision-making process. There is, therefore, a need to combine data pre-processing and data analytics. To understand the data patterns, predictive tools such as a DNN could help to detect the hidden and useful trends in the data that are useful for decision-making [22].

In Nigeria, the implementation of the SDGs is threatened by the prevalence of corruption. In the first instance, corruption promotes social injustices and breeds weak institutions, making it difficult to realize SDG 16 which canvasses strong institutions, peace, justice, and partnerships. In the absence of social justice and strong institutions, achieving national economic plans such as Nigeria's ERPG (2017–2020) and NESP is a mirage [24,34]. This implies that the attainment of the remaining 16 SDGs would be affected. Just as the national economic plans provide platforms for the implementation of the SDGs, the success or failure of the SDG initiatives in a country could be used to evaluate their national plans.

The national corruption survey data that were modelled in this study indicates the need to tackle corruption for people-oriented policies, programs, and projects to be result-oriented. The insights that the application of DNN modeling provides could be harnessed to initiate and implement the value re-orientation programs that will substantially change the country's corruption narrative. Presently, corruption is seen as a culture, rather than being characterized as anti-development by the generality of Nigerians [12,13]. Based on historical antecedents, corruption has entrenched social tensions and unrest is as evident in the prevalence of social vices and non-productive activities such as banditry, militancy, oil bunkering, insurgency, terrorism, kidnapping, and armed robbery with an adverse impact on Africa's largest population and it's second-largest economy [7,13]. As a result, the nation is faced with negative socio-economic indices in critical sectors such as health, education, industry, and agriculture despite its abundant human and material resources [35]. Data can help in addressing these development issues [36].

Implementing the predictive model that is proposed in this study will ensure a proactive approach to solving the corruption menace. Putting it into practice, the model will accurately guide measures that are aimed at nipping in the bud those corruption behaviors whose patterns could be detected by the National Bureau of Statistics [11]. Some anti-graft measures that have been taken in the past to re-orientate Nigerians include road-walk campaigns, the establishment of anti-corruption clubs in schools, etc. The application of a predictive tool can strengthen the effectiveness of these measures.

6. Discussions

The three objectives of the study have been addressed. The study showed how corrupt practices have impacted various policies, programs, and projects in Nigeria with an attendant impact on lives and livelihoods. We also demonstrated how the DNN model could be used to enhance the understanding of patterns in data for an improved anti-corruption drive. Finally, our experiments that involved testing some deep learning optimizers proved that a DNN is reliable as a predictive tool for improving the decision-making process [3,37–39]. Therefore, we are convinced that applying predictive modeling in the drive to implement sustainable development initiatives effectively is worthwhile.

The aim of the study, which is to show that predictive modeling is viable for the attainment of the SDGs, has also been achieved. We empirically showed that the accuracy outcomes of predictive models such as DNNs can be relied upon by decision-makers for proactive and strategic decision-making, particularly in times of emergencies [40–42].

SDG 17 canvasses the use of technology as a means for attaining sustainable development, particularly Information and Communications Technology [43–46]. The role of efficient use of data for driving development has also been emphasized [47,48]. Handling huge amounts of data requires sophisticated techniques like Mapreduce [49–51]. The optimization focus is to get reliable information for optimal decision-making [52–54]. Sustainable development sectors such as education, for example, rely heavily on data and data analysis to drive policies, programs, and projects [55,56]. Machine learning offers added advantage in gaining deeper insights into data using techniques like deep learning [57–59]. DNN uses activation functions and optimization algorithms in eliciting patterns from data [60,61].

Finally, the research question has also been addressed. We have shown that quality decision-making that is based on quality information that is obtained from the application of predictive models can enhance policy formulation, program implementation, and project management in all fields of sustainable development.

7. Conclusions and Future Work

The study has examined the impact of corruption on the attainment of the SDGs, using Nigeria as a case study. We proposed the predictive modeling of development-related data with a view to identifying patterns that could aid proactive and strategic decision-making. Given the significance of the image data in curbing corrupt practices, we experimented with MNIST image data to show the accuracy levels of DNN optimizers.

The outcome of the series of experiments that we performed showed that the DNN stochastic optimizers such as Adam, Adagrad, RMSprop, etc., gave good mean accuracy results: Adam had 98.2% (0.9818); Adadelta 98.4% (0.9840); SGD 94.9% (0.9485); RMSProp 98.1% (0.9809); Adagrad 98.1% (0.9812). This implies that decision-makers can rely on a DNN as a predictive tool for policy formulation, programme implementation, and project management.

In future work, we shall extend the research to other areas to examine how corruption impacts the attainment of the SDGs. We shall also experiment with other neural networks and data dimensions.

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