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A Deep Neural Network-Based Advisory Framework for Attainment of Sustainable Development Goals 1-6

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Abstract: Research in sustainable development, program design and monitoring, and evaluation requires data analytics for the Sustainable Development Goals (SDGs) not to suffer the same fate as the Millennium Development Goals (MDGs). The MDGs were poorly implemented, particularly in developing countries. In the SDGs dispensation, there is a huge amount of development-related data that needs to be harnessed using predictive analytics models such as deep neural networks for timely and unbiased information. The SDGs aim at improving the lives of citizens globally. However, the first six SDGs (SDGs 1-6) are more relevant to developing economies than developed economies. This is because low-resourced countries are still battling with extreme poverty and unacceptable levels of illiteracy occasioned by corruption and poor leadership. Inclusive innovation is a philosophy of SDGs as no one should be left behind in the global economy. The focus of this study is the implementation of SDGs 1-6 in less developed countries. Given their peculiar socio-economic challenges, we proposed a design for a low-budget deep neural network-based sustainable development goals 1-6 (DNNSDGs 1-6) system. The aim is to empower actors implementing SDGs in developing countries with data-based information for robust decision making.

Keywords: sustainability development goals; predictive analytics models; developing economies; deep neural network

1. Introduction

The implementation of the Millennium Development Goals (MDGs) (2000–2015) in developing countries was less than impressive partly because adequate data was not available on the one hand. On the other hand, data analytics models were not applied to the data to detect patterns which human vision cannot detect. Other non-data related challenges responsible for the poor implementation in developing economies include weak institutions, infrastructural deficit and policy inconsistency occasioned by corruption and poor leadership [1,2]. To ensure the data-related problems do not affect the implementation of the Sustainable Development Goals (SDGs), policy formulation and program implementation in various areas need to be enhanced using data analytics [3]. These thematic areas include poverty, hunger, cultural heritage preservation, gender equity, among others. The relative exponential growth in data in the SDGs' life span (2015–2030), when compared with the MDGs period (2000–2015) coupled with advances in artificial intelligence techniques, means big data could be harnessed for developmental purposes. Though SDGs present a broad vision of development goals to be pursued globally for better standards of living for all, the specifics with regards to actions

to be taken to achieve these goals in respective climes are left in the hands of the local (domestic) decision makers [4]. This is because different countries have their unique developmental challenges and opportunities [5]. Hence, local actions in terms of policy formulation, program implementation, and project management have to be articulated within the contextual framework of every country.

Developed economies are more focused on the rather elitist aspects of the SDGs such as climate action (SDG 13) [6,7], life below water (SDG 14), life on land (SDG 15), renewable energy [7], efficient waste disposal systems [8] and urban greening [9]. Conversely, developing countries are faced with overcoming issues articulated in SDGs 1-6 (poverty, hunger, etc.) [2]. Corruption and bad leadership over time are responsible for the socio-economic situation of developing countries [10]. There is growing consciousness among decision-makers in developing economies that the issue of having a national database to provide data on all subject areas is key if the decision on resource allocation is to be scientific and systematic [11]. Hence, in Nigeria, for example, a national bureau of statistics has been set up by the Statistics Act 2007 to coordinate a national statistical information system [12,13].

Nonetheless, having massive data otherwise referred to as big data is not an end itself. In a strict sense, big data refers to making sense out of huge data for reliable and unbiased information for informed decision making [3]. Development in data handling technologies has resulted in the emergence of technologies such as Hadoop and NoSQL that handle both structured and unstructured data efficiently [14]. Hence, massive and highly diversified data being captured at source through the growing use of smart devices such as phones, iPads, laptops, etc. can easily be stored and processed.

Detecting hidden and useful patterns in national data promotes socio-economic planning, growth and development. Artificial intelligence (AI) techniques enhance the process of extracting features from data for purposes of information engineering [15]. One of such AI techniques is machine learning [16]. In this study, we apply deep learning to development-related data using deep neural networks (DNN). DNN is a predictive model that uses multiple layers of computational nodes for extracting features of existing data and relying on patterns learnt to predict the outcome of some future input data [17,18]. The ability to detect patterns in data during the SDGs implementation is a major boost as real-time decisions could be taken by stakeholders, particularly during emergencies to enhance human welfare. This was mostly lacking in developing economies during the implementation of the MDGs.

To ensure that the implementation of the SDGs does not suffer the data-related challenges of the MDGs, this study proposed a DNN-based advisory framework. Public resources meant for alleviating poverty, tackling diseases, curbing unemployment and addressing other social-economic issues peculiar to developing countries can be optimized by effective and efficient decision-making based on precise information—this study aimed at empowering SDG implementation actors with precise data-based information using predictive analytics. We used a deep neural network and demonstrated its potential as a viable predictive analytics tool in the implementation of SDGs 1-6.

The objectives of this work include:

1. Identify poor usage of data as partly responsible for the inadequate implementation of previous global sustainable development plans like the MDGs (2000–2015).
2. Explain the importance of extracting hidden and useful patterns in development-related data for informed decision-making.
3. Show that machine learning tools like deep neural networks can be used for extracting and predicting patterns in historical data.
4. Design a data analytics advisory framework that uses deep neural networks for extracting information from existing data for enhanced decision-making.
5. Explain how the deep neural network-based advisory framework is helpful in the implementation of SDGs 1-6 in developing economies.
6. Explain how data analytics can improve the implementation of present and future global sustainable development plans like the SDGs (2015–2030).

In summary, the attainment of SDGs 1-6 in developing economies can be facilitated by integrating a predictive analytics model into the sustainability protocols. Our work proposes a DNN-based system for this purpose. We also explain how this proposed system functions.

The paper is arranged as follows: In Section 2, a literature review is done. In Section 3, the methodology is outlined while in Section 4, we discuss implementation and results. Section 5 contains the implications of the proposed system for the attainment of SDGs in developing economies while in Section 6, the conclusion outlines how the study objectives were achieved.

2. Literature Review

2.1. Context of Deep Neural Networks

Deep learning is also called hierarchical learning or deep structured learning. It is one of the machine learning methods that is based on artificial neural networks. It uses multiple layers of computational neurons for extracting features of existing data for the purpose of predicting the outcome of future data [17]. The three categories of learning are unsupervised, supervised, and semi-supervised [19].

Popular architectures for deep learning include deep belief networks, deep neural networks (DNN), convolutional neural networks and recurrent neural networks, though the most popularly used is DNN [20]. These architectures have been used to solve problems in fields like speech recognition, computer vision, audio recognition, natural language processing, machine translation, social network filtering, drug design, bioinformatics, medical image analysis, board game programs and material inspection. In these fields, they have generated outcomes that are sometimes better than those of human experts.

The distributed communication and information processing nodes of biological systems inspired artificial neural networks (ANNs) though there are differences between them. While the biological brain is analogue and dynamic, ANNs are static and symbolic [21].

2.2. Time Series

DNN operations involve a training stage, testing stage, and working stage in that respective order. Because training must happen before testing, and testing must precede the working stage, there is a time-base sequential order. Hence, deep learning is a time series forecasting technique.

In a strict sense, a time series is a set of data points arranged in time order. It is a sequence captured at regularly spaced points in time and could be referred to as an arrangement of discrete-time data. Examples include counts of sunspots, heights of ocean tides, and stock exchange market figures.

Time series *analysis* is made up of methods that analyse time-series data in a bid to extract useful statistics and other data characteristics. The term time series *forecasting* refers to the use of a model to predict future values based on values observed previously. Time series analysis is applicable to a range of data such as discrete numeric data, real-valued continuous data, and discrete symbolic data (sequences of characters like letters and words) [22].

2.3. Sustainable Development Goals

Lawrence [23] advocates for the improved coordination of scientific efforts towards achieving the SDGs. The paper also identified the authenticity of data collected as one of the major factors that militated against the implementation of MDGs in Nigeria, which has the potential to derail SDG programs. Other factors include overpopulation, religious dogmatism, ignorance and superstition, lack of political will, corruption and economic mismanagement. These internal issues apart, there are external threats which include the production of weapons of mass destruction which may be chemical, biological, cyber, or nuclear. There is a need for the United Nations to scale up legislation that prevents the proliferation of arms. Improving the quality of education is also key for achieving the SDGs. To consolidate on the advocacy for stepping up scientific efforts for the attainment of the SDGs,

our present study proposes the use of predictive modelling using deep neural networks for evaluating and achieving SDGs. Though highly scientific and mathematical, it provides decision-makers and actors with unbiased and timely information for proactive decision-making based on patterns recognized in existing data.

2.4. Related Works

Glorot and Bengio in [24] studied deep neural networks from the viewpoint of initialization of network parameters with the aim of expediting convergence. Their efforts culminated in a new initialization scheme which has been shown to result in faster convergence. The authors posited that since 2006, many algorithms had been successfully used to train DNN with evidence of experimental results that show the superiority of deeper over less deep architectures. The quest for better knowledge for improved algorithms made them realize that non-linear activations' functions had significant impact. The authors mainly focused on improving the convergence rate by fine-tuning activation functions. They did not show how the application DNN in sustainable development could enhance the implementation of policies and programs. In this present study, we aim at using DNN as a knowledge engineering tool to elicit hidden and relevant information from historical data. The essence is to empower implementation actors of SDGs with accurate information for efficient decision-making.

Meadows [25] suggested that information systems are critical to assessing development and sustainability. It was acknowledged that these are old problems even though they appear and re-appear together at different times on a global scale and in an urgent time frame. The author opined that for better relevance, sustainability indicators must be about time and thresholds rather than mere environmental indicators. In the same vein, development indicators should be about equity, efficiency, sufficiency and quality of life instead of just being growth indicators. However, the work did not examine sustainability and development in the context of global economic frameworks like the Millennium Development Goals (MDGs) (2000–2015) and Sustainable Development Goals (2015–2030). The study also failed to identify improper handling of data as one of the causes of the not-too-impressive implementation of earlier global economic plans like the MDGs. In this study, we emphasized that data and knowledge engineering are key to the successful implementation of global economic plans. We formulated sustainable development as a machine learning problem and proposed a DNN-based framework for extracting information from existing development-related data.

In [26], it was mentioned that the design, monitoring and evaluation of sustainable development programs had been boosted by the rise in use of information technologies like tablets, smartphones, and automatic sensors. These devices aid the processes of collecting, analyzing and disseminating data and information. Additionally, there is exponential growth in the availability of big data which encompasses phone records, satellite images, analysis of electronic financial transactions and analysis of tweets and social media. The authors also observed that information can now be collected faster, more cheaply, and made available in real-time to development stakeholders for providing early warnings of man-made and natural emergencies. Though the work stressed the importance of data and data analytics in development, it did not emphasize how the short supply of data and data analytics adversely affected the successful implementation of global sustainable development plans like the MDGs. It also did not suggest how this could be corrected in the present and future global economic plans. In the current study, we address these gaps by advocating for the incorporation of predictive analytics in sustainability protocols for the implementation of both the ongoing global SDG plan and future economic plans.

Guterres [27] offers evidence-based insights into appropriate actions to be taken for the achievement of the SDGs. The author defined a sustainable world as one where all people live productive, vibrant and peaceful lives and emphasized that the 2030 Agenda offers a blueprint for shared prosperity. To ensure that governments respond to the integrated and transformative 2030 agenda, the United Nations is repositioning its development systems to meet their needs. To unfold the required economic and social transformation, the paper highlights areas that are potent in driving progress across all the

17 SDGs. They include better use of data, resilience, financing, local action, sustainable and inclusive economies, effective institutions, and leveraging on science, technology and innovation with particular emphasis on digital transformation. To fast-track delivery for people and the planet, the author advocates that policy choices should leave no one behind. Despite underscoring the role of data and technology in the implementation of SDGs, the work did not categorically mention how hidden and useful information could be extracted from existing data. Such unbiased information could be useful for the design, monitoring and evaluation of SDG policies and programs at national and sub-national levels. This present study applies predictive modelling for the purpose of eliciting relevant information from historical data.

Among the above-reviewed works, none have addressed the data-related challenges that confronted the implementation of the MDGs [3,23], resulting in ineffective and inefficient implementation. To ensure that the implementation of SDGs is not plagued by the same challenges, our study concentrates on resolving this issue by proposing a machine learning-based technique. The DNN technique extracts relevant information from existing development-related data for robust and real-time decision-making by implementation actors of SDGs. We also propose that data analytics be integrated into sustainability protocols for the smooth implementation of future global sustainable development plans.

3. Methodology

The present study used Nigeria as a case study. The country has a number of agencies and plans such as the National Directorate of Employment (NDE) and National Economic Growth and Recovery Plan (NEGRP) that are aimed at tackling poverty, unemployment, and hunger [13,23,28]. The country's national bureau of statistics offers statistics for planning in all spheres of socio-economic and political development [12]. There is also increased research focus such as the implementation of SDG 6 in Nigeria, as explained in [29]. The application of data analytics to sustainable development data would enhance research, program design and evaluation of the SDGs [26]. This will, in turn, facilitate the attainment of the goals in different climes. Data analytics technique such as DNN can forecast the outcome of future data based on the observed characteristics of existing data. The essence is to make timely and accurate information available to SDG implementation actors, as indicated in Figure 1 below.

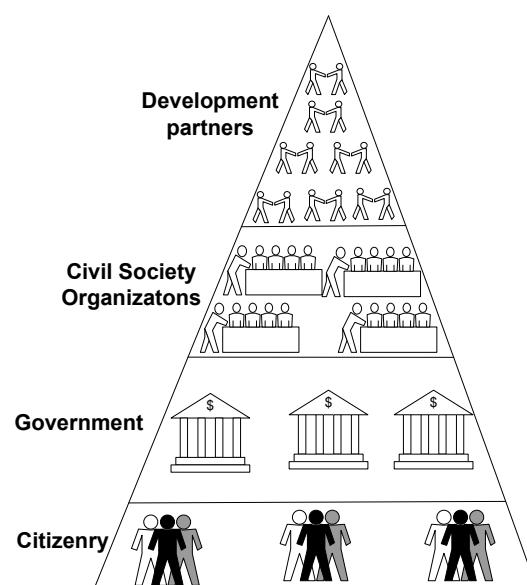


Figure 1. Granularity layers of Sustainable Development Goals (SDGs) implementation actors.

The various critical stakeholders as shown in Figure 1 can benefit from a data analytics system; The citizens rely on a data analytics system to obtain information on the viability of policies, programs and projects designed to improve their lives. The government can secure information from the system for designing sustainable development initiatives that impact positively on lives and livelihoods. Civil society organizations can rely on patterns in exiting data for measuring, monitoring, and evaluating sustainable development efforts of the government. Finally, the system can avail development partners with information on challenges and prospects of development initiatives for strategic interventions.

In the spirit of inclusive innovation which brings all on board, developing countries across Africa, Asia and South America are the target of this system. This is in view of their unique developmental challenges and the particular relevance of SDGs 1-6 in their socio-economic situation. We consider that the success of the 2030 Agenda is partly dependent on data-based information systems. The stages for designing the proposed deep neural network-based SDG (DNNSDG 1-6) system are as follows:

3.1. Requirements Analysis

Actors who would implement SDGs 1-6 in developing economies need timely and unbiased information which a deep neural network-based system can offer from historical data [30]. As shown in the entity-relationship diagram (ERD) in Figure 2 below, the actors or stakeholders would need to be armed with information on the targets and indicators of SDGs 1-6. This would ensure that policies and programs in national and sub-national plans are monitored and evaluated in the context of these globally outlined parameters as a baseline for benchmarking results and intensifying efforts.

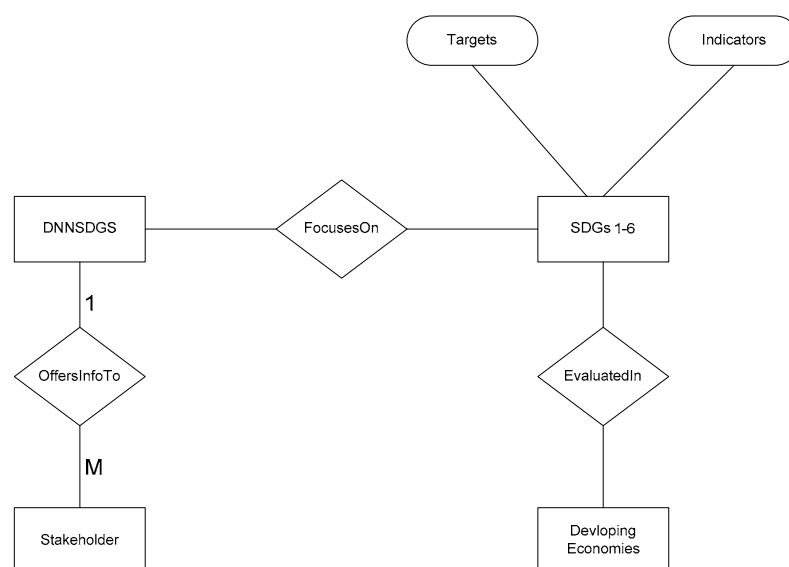


Figure 2. Entity-relationship diagram showing SDGs 1-6 programmes implementation entities.

Our study used observation and interview as requirements engineering tools [31] to identify both functional and non-functional (quality) requirements of the proposed deep neural network-based SDGs 1-6 (DNNSDGs1-6) system.

In the Use Case diagram in Figure 3 below, we show that the functional requirements of SDGs 1-6 actors include Information Services, Entity/Concept Relationship Mining, Data Segmentation/Clusterization Services, Data Categorization/Classification Services, Data-based Prediction/Planning Services.

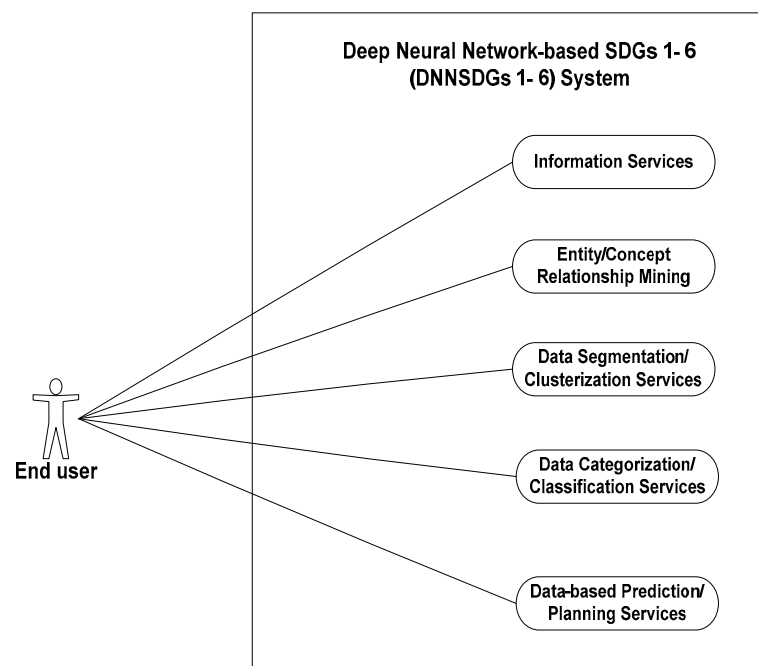


Figure 3. DNNSDGs1-6 Use Case diagram.

The end-user in the context of SDGs program research, design, monitoring and evaluation is anybody seeking advisory services from DNNSDGs1-6. The user could be an ordinary citizen, government official, non-state actor, or development partner (international organization). The user is a stakeholder in policies, programs and projects that enhance implementation of SDGs 1-6. Examples of services rendered include:

Information Services ()—for example, DNNSDGs1-6 would offer information on corruption statistics to researchers studying corruption patterns and proffering solutions so as to promote peace, social justices and strong institutions for tackling poverty and hunger.

Entity/Concept Relationship Mining ()—for example, DNNSDGs1-6 should offer advisory on programs/projects that should be executed before the commencement of others.

Data Segmentation/Clusterization Services ()—for example, it advises on programs/projects that could be grouped during implementation for optimal resource utilization.

Data Categorization/Classification Services ()—The system, for example, can offer advice on proper program/project classification scheme to enhance monitoring and evaluation.

Data-based Prediction/Planning Services ()—For example, government and citizens could be advised on whether a program/project would fail given the budget, competencies of handlers, prevailing economic situation, inflation rate, etc. based on historical data.

3.2. System and Software Design

We show in Figure 4 an n-tier architecture of DNNSDGs with three layers (presentation layer, services layer, and the data layer [32,33]. SDGs implementation actors who are to use the proposed system would at the Presentation Layer use mobile and fixed devices such as desktop, laptop, smartphone, iPhone, etc. to access the system for advisory services. The Web Services and Middleware are accommodated in the Service Layer. In the Web Services compartment, there are components like Data Management, Security, Search, Relationship Management, Predictive Analytics and Clustering. Policies are outlined in Data Management to ascertain the owner of data and determine how data would be shared among collaborating developing countries. This is to solve the problem of data handling and ownership experienced in such a system. As the SDGs implementation actors collaborate in shared information, the Security component protects their privacies as well as ensures the ethical

usage of data by providing data manipulation guidelines. Users of DNNSDGs1-6 are empowered to search and get information by the Search component. Insights into useful patterns in the humungous data are facilitated by the remaining components such as Relationship Mining, Predictive Analytics and Clustering. We expect that regarding SDGs 1-6, the stakeholders in the developing economies who would collaborate on this platform are likely to use different technology platforms. To guarantee seamless interactions among the heterogeneous platforms and programs (software), the Middleware compartment contains a set of middleware with different uses. For example, the Home Grown middleware is tailor-made for catering to specific interoperability requirements of DNNSDGs. At the same time, RPC/ORB (Request Procedure Call/Object Request Broker) concentrates on distributed applications that are synchronous. Messaging-based real communication is handled by Pub/Sub (Publish/Subscribe) while Message Queuing facilitates robust communication based on messaging. TP Monitors (Transaction Processing Monitors) coordinates processes and significantly reliable transactions in the DNNSDG1-6 system. In the Data Layer, we have databases for the respective SDGs 1-6 (i.e., SDG 1 database, SDG 2 database, ... SDG 6 database). Each database contains a large dataset of activities in a particular subject area (e.g., data on poverty contained in SDG 1 database).

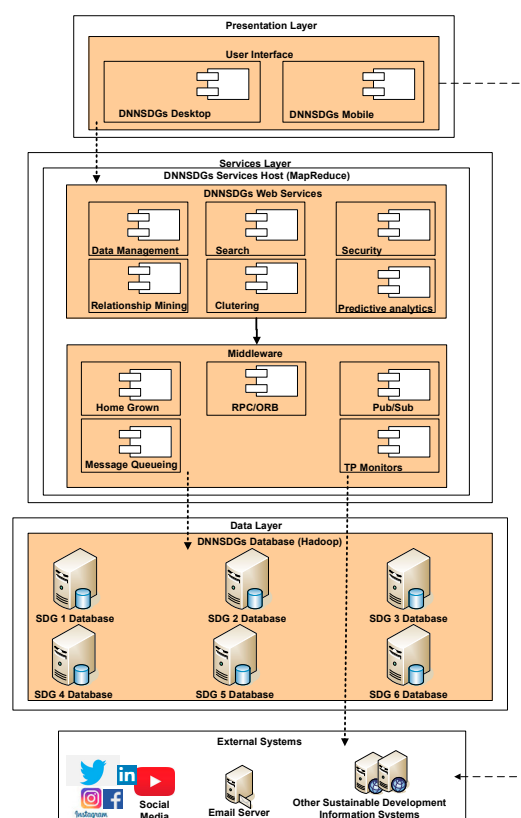


Figure 4. DNNSDGs1-6 n-tier Layered Architecture.

As shown in Figure 4 above, the DNNSDGs1-6 is expected to have a handshake with external systems like social media (Facebook, Twitter, GooglePlus, Instagram, YouTube), email systems and other sustainable development information systems.

As part of our advocacy for the United Nations to pay special attention to developing countries with limited opportunities and peculiar socio-economic challenges, we propose a computer network in this regard. Figure 5 below is a computer network perspective of the proposed data analytics system which we christened United Nations Sustainable Development Goals 1-6 Network (UNSDGs1-6N). For effectiveness and efficiency, UNSDGs1-6N is designed as a distributed and parallel computing system with Hadoop MapReduce implementation [34]. The network architecture comprises three grid networks, representing three continents with developing economies (Africa, Asia, and South America).

The three regional networks are connected to UNSDGs1-6N. In every grid network, there is a distributed file system, a Hadoop master server, load balancer, file server, and three Hadoop application servers [35].

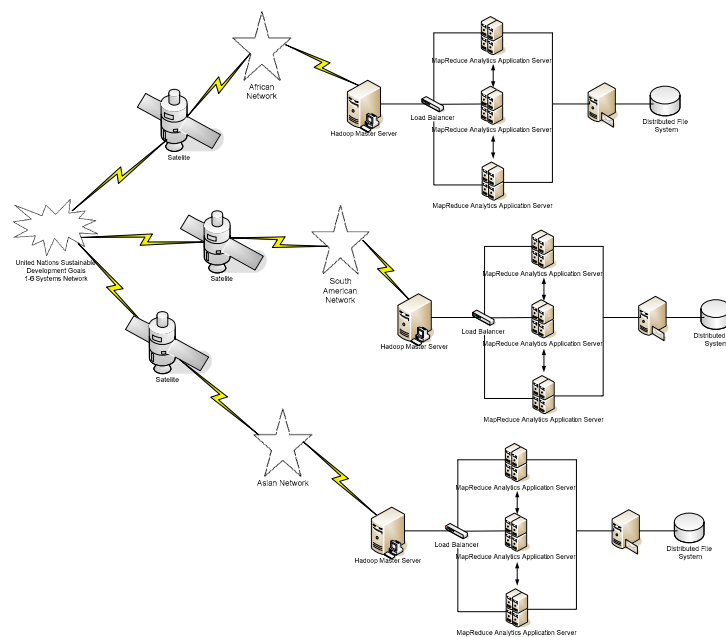


Figure 5. United Nations Sustainable Development Goals 1-6 Network.

Implementation actors of SDGs 1-6 in the various developing countries take local decisions on programs and projects that uplift the lives of their people, and they compare notes using the SDGs targets and indicators [36] as benchmarks. They need data-based information to deliver people-oriented and result-oriented services as articulated in the distributed and parallel computing model (Figure 5). Huge data would be generated and processed as developmental activities are going on, and MapReduce technology has been incorporated in the model for this purpose. The entire data analytics set up is to ensure the parallel and distributed processing of big data in a manner that guarantees high availability, high performance, ease of support/maintenance and robust fault-tolerance [37]. When queries are received from stakeholders on sustainable development programs and projects, they are split and processed in parallel as typical of Map operations. Thereafter, Reduce operation is applied so that outcomes are aggregated as a single output. Typical MapReduce implementation leverages on predictive models like deep neural networks, decision tree classifier, and Naive Bayesian probability for predicting behavior and outcome [38]. It can also use algorithms like fuzzy logic and binary logic for ascertaining relationship and dependency among program variables [39]. Consequently, precise and incisive information on budget, the suitability of programs, competencies of project contractors/consultants, delivery expectations, and other programs/projects related considerations could be generated for relevant and critical stakeholders and sustainable development actors. The ultimate goal is to guarantee informed decisions. This way, data analytics would affect program design, delivery and evaluation positively.

4. Implementation and Results

Deep learning is gaining a lot of attention owing to its massive use in solving problems that were previously considered impossible or extremely difficult. Big data generated by SDG stakeholders range from text, to images to audio which could be used to evaluate development programs. There is a need to improve the capacity of SDG implementation actors for detecting useful patterns in existing data. This will facilitate strategic decision-making in the implementation of SDGs 1-6, which are more relevant to developing economies. Hence, we proposed and designed a deep learning neural

network-based advisory framework. Other areas where deep learning has been successfully applied include diagnosis of diseases, propelling self-driving cars, and image generation [17].

The implementation of poverty alleviation and employment generation policies, programs and projects is the cardinal focus of SDGs 1-6. Nigeria has a number of policy measures in this regard [23]. These activities often involve the use of image data to validate individuals and ensure that social safety net packages get to target beneficiaries. Image data used for such authentication purposes include biometrics—e.g., fingerprints, eye (iris). To demonstrate the use of the deep neural network in image processing, we experimented with a standard dataset of images called Modified National Institute of Standards and Technology (MNIST) database [40]. MNIST is a standardized dataset of images of handwritten digits. The experiments were executed with selected stochastic gradient descent algorithms using Python deep learning libraries [41]. Gradient descent is the choice algorithm for training DNN [17]. Gradient descent algorithms are also referred to as optimizers since the DNN training process is purely an error optimization process. Visuals that illustrate the performances of deep learning algorithms like Adam, RMSProp, and AdaGrad, among others, can be presented in the form of graphs using any of these Python deep learning libraries. They also support the pictorials of complicated graphs and animations. All these make comprehension of outcomes easy for SDGs implementation actors who may not be data analytics specialists. For our experiments, we used the Keras application programming interface (API), Tensorflow, and Convolutional Neural Network [42] as our DNN model.

The optimizers executed are stochastic gradient descent algorithms that iteratively and randomly pick a data item, train on it and generate a predicted outcome using internal parameters that are randomly initialized [17]. The optimizers are Adam, Adagrad, Adadelta, RMSProp, and SGD and the outcomes of the experiments are summarised in Tables 1–3.

Table 1. Training time (in seconds).

Optimiser	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th	14th	15th	16th	Total
SGD	83	78	95	95	94	94	94	87	87	86	88	103	98	91	88	87	1843
Adagrad	86	82	103	114	104	104	104	102	113	109	109	110	106	105	106	109	2150
Adadelta	127	121	145	145	152	138	131	139	135	129	130	133	135	145	139	126	2847
RMSProp	95	88	109	107	108	107	106	116	115	109	106	108	107	108	110	110	2153
Adam	110	106	125	125	125	127	125	125	127	126	123	121	121	115	119	122	2406

Training time is a measure of the time required for the complete training of DNN per iteration. The loss function is the difference between actual output and predicted output, while accuracy measures the degree of the preciseness of prediction. The differences in training time, loss function and accuracy as shown in Tables 1–3 suggest varying levels of performance, and underscore why some optimizers are preferred to others in the training of DNN. Though accuracy is the most important metrics, training time becomes more relevant as a metrics with huge amount of data. The number of times a system is trained is at the discretion of the machine learning enthusiast.

Though extraction of information from existing data for enhanced decision-making embraces services shown in Figure 3 such as Information Services, Entity/Concept Relationship Mining, Data Segmentation/Clusterization Services, Data Categorization/Classification Services, and Data-based Prediction/Planning Services, our experiments explored mainly the prediction capabilities.

Table 2. Loss function.

Optimiser	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th	14th	15th	16th
SGD	0.5094	0.2330	0.1814	0.1534	0.1380	0.1231	0.1144	0.1058	0.0979	0.0929	0.0891	0.0823	0.0799	0.0766	0.0736	0.0694
Adagrad	0.1858	0.0906	0.0696	0.0576	0.0499	0.0451	0.0403	0.0364	0.0338	0.0308	0.0281	0.0261	0.0249	0.0232	0.0220	0.0212
Adadelta	0.1998	0.0806	0.0575	0.0436	0.0368	0.0302	0.0253	0.0232	0.0185	0.0171	0.0137	0.0125	0.0119	0.0104	0.0095	0.0090
RMSProp	0.2057	0.0882	0.0664	0.0586	0.0507	0.0455	0.0426	0.0349	0.0340	0.0302	0.0267	0.0259	0.0247	0.0217	0.0223	0.0206
Adam	0.2183	0.0891	0.0635	0.0504	0.0389	0.0328	0.0278	0.0248	0.0216	0.0190	0.0181	0.0178	0.0155	0.0141	0.0152	0.0133

Table 3. Accuracy.

Optimiser	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th	14th	15th	16th
SGD	0.8565	0.9305	0.9464	0.9544	0.9586	0.9625	0.9658	0.9689	0.9700	0.9713	0.9721	0.9746	0.9756	0.9762	0.9772	0.9784
Adagrad	0.9448	0.9738	0.9793	0.9830	0.9853	0.9863	0.9881	0.9896	0.9901	0.9912	0.9921	0.9924	0.9930	0.9935	0.9938	0.9941
Adadelta	0.9408	0.9760	0.9828	0.9863	0.9890	0.9909	0.9924	0.9928	0.9940	0.9948	0.9958	0.9958	0.9964	0.9963	0.9970	0.9970
RMSProp	0.9378	0.9739	0.9806	0.9835	0.9860	0.9870	0.9887	0.9898	0.9902	0.9915	0.9925	0.9933	0.9936	0.9943	0.9946	0.9947
Adam	0.9353	0.9726	0.9803	0.9842	0.9875	0.9894	0.9906	0.9913	0.9928	0.9937	0.9940	0.9939	0.9949	0.9952	0.9947	0.9953

Interpretation, Observation and Inference

In Table 1, we present performances of the five algorithms with respect to training time. For the 16 iterations performed, SGD has the lowest (best) combined training time of 1843 s while Adadelta has the longest (worst) training time of 2847 s. Training time as a measure of performance is relevant because implementation actors of SDGs that are to rely on the DNN-based system for advisory may be discouraged if the time it takes to secure information from the system is long.

Table 2 shows that Adadelta has the best loss value of 0.0090, while SGD has the worst loss value of 0.0694. This is a measure of the difference between the actual value and predicted value. A low loss value means the predictive system can give very high accuracy in its predictions, and a high loss value implies a low accuracy level of predictions. Hence, the accuracy and loss value is indirectly proportional. This assertion is further confirmed in Table 3, which measured accuracy. At the 16th iteration, for example, SDG has the lowest accuracy of 0.9784 (97.84%) while Adadelta has the highest accuracy figure of 0.9970 (99.70%).

Of the three parameters measured above (training time, loss function and accuracy), the most relevant for decision-making is accuracy. This is because every policymaker in the sustainable development domain wants to be sure of the impact of a decision made on the welfare and wellbeing of citizens. The high accuracy of prediction, as demonstrated by all the algorithms as shown in Table 3 (with lowest of 97.84% and highest of 99.70% at the 16th iteration), is a testament to the fact that deep learning is a reliable decision-making tool. Hence, SDG implementation actors can rely on it for accurate predictions that aid proactive measures, particularly in times of emergencies (health, humanitarian, financial, environmental and socio-economic emergencies). It is expected that this will boost the implementation of SDGs 1-6 in developing countries and impact directly on lives and livelihoods. Our proposal for a low-budget predictive analytics framework that targets the implementation of SDGs 1-6 in less developed countries takes into cognizance the relatively limited opportunities and scarce resources of these countries.

Specifically, in terms of quality loss (or accuracy), Adadelta performed best, while with regard to training time, SGD performed best. Therefore, there is a window of opportunity for upcoming researchers to propose new algorithms that harness the strengths of Adadelta and SGD as a possible improvement. This will make deep learning more attractive to stakeholders like SDGs implementation actors who have a 2030 target to meet.

5. Implications of DNNSDGs for Actualization of SDGs in Developing Economies

Many developed economies have integrated data analytics in their national and sub-national economic plans, while developing economies are only known to be rich in data [43]. This is partly because of the huge population whose socio-economic activities generate big data. However, organized data in the form of a national database is lacking in many developing countries [2]. Absence of national database apart, even the existing fragmented datasets are not reliable as the faulty process of data collection and preparation introduces noisy data. Since a good decision is based on good data, this is a challenge. Yet another shortcoming is the lack of integrated predictive systems in national and sub-national sustainable development plans. This implies that developing countries have not substantially leveraged on artificial intelligence for policy formulation, program implementation, and project management. All these make it difficult for sustainable development stakeholders to harness the potentials of data for development. However, the narrative is changing as there is a growing quest for many SDG signatory nations to align their national development plans with the global SDG plan. As a result, developing economies are establishing national statistical information systems coordinated by the national bureau of statistics. In Nigeria, for example, this is backed by an Act of the state [12,13].

Big data is not just about the volume of data at the disposal of a nation. More importantly, it connotes the value derivable from it. Our proposed DNNSDG1-6 system is aimed at strengthening the capacity of developing economies to use artificial intelligence to elicit hidden and useful information in national

databases for putting their economies on the path of sustainable development. We advocate that implementation actors of SDGs in various developing countries engaged in program research, design, delivery and evaluation for the welfare and wellbeing of their citizens should be guided by patterns in their national data. The machine learning technique we used in designing DNNSDG1-6 has been proven to be effective for detecting patterns in data [17]. This makes planning and implementation of programs to be scientific and systematic for optimal utilization of scarce public resources. We reiterate that data analytics is needed to make sense of data and strongly advocate the incorporation of predictive models in sustainability protocols. Studies have shown that predictive models like deep neural networks, Naïve Bayes and decision tree classifiers are good data analytics tools for detecting useful patterns in historical data for the purpose of predicting the outcome of future data [18].

Therefore, if implemented, our proposed DNNSDGs1-6 system which targets developing economies in the spirit of inclusive innovation will empower domestic decision-makers. They will have at their disposal unbiased and reliable data-based information for taking timely decisions. This will impact positively on the efficiency of proactive and strategic measures and actions aimed at accomplishing the SDGs 1-6 targets.

Discussion

The objectives of this work, as stated earlier, have been addressed. With literature proofs, we have highlighted that weak institutions, infrastructure deficit and policy inconsistency are the banes of developing economies. We also identified the causes of these problems as corruption and poor leadership. We explained that these problems have resulted in poverty and hunger, making the satisfaction of basic needs of life as captured in SDGs 1-6 still the priority of developing countries.

Our study also identified factors responsible for the ineffective implementation of previous global sustainable development plans like the MDGs to include inadequate data availability and the inability to extract intelligence from existing data for robust decision-making. Intelligence gathered can be useful for Information Services, Entity/Concept Relationship Mining, Data Segmentation/Clusterization Services, Data Categorization/Classification Services, and Data-based Prediction/Planning Services.

To address this problem, we have proposed and designed a DNN-based advisory system called DNNSDGs1-6. The system uses machine learning (deep learning) for eliciting hidden and useful information from historical data. Though we focused mainly on prediction services in our experiments, other services as identified in the Use Case diagram (Figure 3) can be rendered by the DNNSDGs1-6 system.

In addition, we identified image data as critical in the verification and validation of persons scheduled as beneficiaries of social safety net packages. The numerous social protection programs in Nigeria (like any other developing country) are sustainable development initiatives aimed at ensuring that no one is left behind in tandem with the philosophy of the United Nations SDGs (2015–2030). The study demonstrated that deep neural network could be used to accurately predict patterns in image data for enhanced decision-making.

6. Conclusions and Further Work

This work examined the first six SDGs, which are more relevant to developing economies than the developed countries owing to limited opportunities in the former. To draw the attention of development partners such as the United Nations to the needs of these low-income countries, and inclusive innovation approach was proposed. Another motivation for proposing the new approach is to show that the problem of extracting information from data which affected the implementation of previous global plans like the MDGs could be tackled. The approach involves designing a DNNSDGs1-6 system that uses deep neural networks as a predictive model for eliciting useful patterns in big data. The unbiased information generated could be used by local decision-makers implementing SDGs 1-6 in their respective climes for effective and efficient decisions aimed at optimal utilization of public resources. This way, sustainable development programs could be made more result-oriented and

people-friendly. By extension, the use of data analytics frameworks like our proposed DNNSDGs1-6 can improve the implementation of present and future global sustainable development plans like the SDGs (2015–2030).

We envisage that developing countries may inter-relate in implementing regional and sub-regional socio-economic programs. To solve the problems of usability and interoperability in a system that integrates various countries with different technology platforms, we integrated middleware and a data handling technology (Hadoop MapReduce—A NoSQL technology) in the proposed system.

Research in sustainable development is tending towards harnessing big data for program design, delivery and evaluation [26]. In this regard, SDG actors are increasingly seeking technologies that offer them useful insights into the big data at their disposal. There is, therefore, a need for AI experts to intensify research in the areas of making expert systems more attractive for usage. For instance, deep learning is still confronted by problems of quality loss and prolonged training time [24]. These issues are occasioned by the sparse gradient [44], decreasing learning rate [45,46], presence of many poor local optima [47], high variance in parameter updates [48] and saddle points [49]. Future research should focus on resolving these problems for a richer user AI experience.

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