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Machine Learning Competencies Development

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Abstract

In this information age, there are several competencies and skillsets seeking the attention of learners. One such competency is Machine Learning (ML). This manuscript showcases the tools, algorithms and practical application of ML in Electrical technology, construction, health care, and flood control. By mining and analysing data from two (2) search engines, and corporate websites, this manuscript showcased practical use cases of ML. Based on these real-world applications, deductions were made on how ML competencies can be developed. Likewise, recommendations on strategies that would enhance productive ML research and utilisation in electrical/electronic technology education were outlined.

Keywords: *Machine Learning, electrical technology, Competency development, Education*

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Background to the Study

The 21st Century in Nigeria and Africa is characterised by unemployment (Chidiebere et al., 2014; Ordu, 2020; Ordu & Abdulkarim, 2017), an outburst of information and literacy (Igbinovia et al., 2021), knowledge-driven economy (Ordu, 2020), the increasing need for publicly accessible and available datasets about critical economic indicators, and rise of Fin-Techs and technological Startups (Ordu & James, 2019). The challenge of graduate unemployment in the midst of several traditional jobs has raised several questions and propositions. Challenges like these have stimulated and compelled local and international academic institutions to embrace entrepreneurship education across its programmes (Bauman & Lucy, 2021; Oberer & Erkollar, 2023; Ordu & Abdulkarim, 2017; Papageorgiou et al., 2021; Sibanda & Naidoo, 2023).

This diversity of information and rising literacy amongst families and communities comes with an attendant barrage of questions that need to be contextually answered to dissolve misconceptions and misunderstandings. In an attempt to provide the answers some have taken the route of the blame game (Federal University Otuoke, 2024) while others have sought to provide hands-on-training opportunities (Federal University Otuoke, 2024; Ordu & James, 2019). Big Data gathered from students' academic performance, graduate project reports, business transaction, road/air and waterways logistics, real estate, educational policies, political activities, sports, religious activities, social activities, and economic activities are all demanding for storage, interpretation, and application; sometimes, even competing. Who will arise to the task? One who is competent in the technological skills of this decade can rise to the task. Being able to identify and cease such an opportunity means that he/she possesses some entrepreneurial competencies.

New challenges require a deep understanding of the challenge, knowledge of the potential solutions, and critical evaluation to choose the most appropriate solution from the potential solutions. Hence, James (2024) proposed three steps to promote deep learning. This included use of repetition, use of appropriate contextual examples, and provision of prompt feedback to learners.

Competency development can be said to be closely related to effective use of instructions, corrections, reproofs, and commendations. These four elements can be found in the toolbox of every educator. But, one educator varies from another in his/her effective and efficient use of the tools. However, learning can be self-directed or instructor-led ""(Malec, 2022; Robinson & Persky, 2020; Voskamp et al., 2022). Thanks to this information decade, the individual who desires to develop any competency is no longer restricted to the four walls of an academic institution or library. Data, information, tools, and illustrations are readily available at the click of a button. Now, the individual's major task lies in his/her ability to cultivate and maintain a healthy environment and network that promotes the achievement of his/her stated goals. It is important to note here that self-directed learning does not erase the need for a teacher at some point. This is because, the teacher and affiliated institutions create the logical consistency and structure, as well as the learning materials needed by the self-directed learner. The second aspect – structure of content – is often effectively provided by an

institution. And such an institution should comprise a team of educators and related practitioners.

Leaving the task of skillsets development or competencies development at the doorstep of the educator alone can become an individual's own undoing. While educators, institutions and the community indeed can influence the self-directed learner, the commitment and dexterity of the learner is non-negotiable. Moreover, nature reveals three things from the pointing of the finger: 1) Others are 20% responsible for the outcome of one's life. 2) The Unseen is 20% responsible for the outcome of one's life. 3) The individual is 60% responsible for the outcome of his/her life. Therefore, to achieve the set-out goal, an individual need to maximise all three dimensions as they tackle contemporary challenges, and the society would become a desirable place to live in, work, learn, and tour.

Skills and competencies are best developed by a learner, student or researcher when he/she has found an area of application or of interest. Therefore, this manuscript highlights some of the areas in which machine learning is being applied. This would inspire its audience about the strategies to adopt to develop similar skillsets and competencies. Also, skills required in recent job market opportunities can be traced to machine learning competencies. Hence, academic programmes in electrical technology education needs to create room for and accommodate these in order to stay relevant.

This manuscript highlights the technological skillsets of the information decade with a focus on machine learning and the discipline of electrical technology. Although the topic and related concepts finds cross-disciplinary application and global significance, this manuscript ia focused on electrical technology case studies, and other sectors with national and international examples. By reviewing the reports and publications of scholars and experts, "Machine Learning Competencies Development" positively transforms the 21st Century Nigerian and African student or researcher and indeed communities and nations. With the influence of the case studies and examples, this manuscript provides a succinct overview of notable applications of Machine Learning to stimulate machine learning competencies development strategies and drive electrical technology education curriculum review.

Problem Statement

Along with its disruptive innovations, this decade of information raises uncertainties in all sphere of human endeavour: education, agriculture, medicine and healthcare, science and technology, arts and culture, sports and recreation, the environment, and social development amongst others. In the education industry, learners, students and researchers alike face a myriad of skillsets and competencies required to perform tasks and to maximise business intelligence. No matter the profession, there is a common objective amongst learners: attain a contemporary skill, and practice his/her profession profitably. But developing a competency requires knowledge of the tools, techniques, and the application of such a competency. Hence, this manuscript by reviewing and highlighting current applications of machine learning unveils the tools, techniques, platforms and use-cases needed to develop machine learning competencies.

Research Objectives

The 21st century and this information decade demands certain skills with entrepreneurial competencies. Hence, the following specific objectives were pursued:

1. Identify technological skillsets of this decade.
2. Review applications of machine learning.
3. Highlight strategies to develop Machine Learning competencies.

Research Questions

To achieve the sated specific objectives, the following research questions were pursued:

1. What are the technological skillsets of this decade?
2. What are the applications of machine learning?
3. How can Machine Learning competencies be developed?

Skillsets of the Information Decade

This 21st century and decade of digital transformation is characterized by an increasing transformation of traditional processes unto the digital platform. It can be observed that traditional tasks like education or buying and selling amongst many others are constantly being modelled and performed in the digital space with increasing precision, accuracy, and large-scale adoption. In the light of this, the skillsets demanded by this century and decade are both technical and soft.

Table 1: Technical and Soft Skills of the Information Decade

Generative AI	Technical Skills	Soft Skills
Gemini	Artificial Intelligence and Machine Learning, Data Literacy and Analysis, Cybersecurity, Cloud Computing, Software Development and Digital Proficiency,	Critical Thinking and Problem-Solving, Adaptability and Resilience, Communication and Collaboration, Ethical Awareness, Continuous Learning, Emotional Intelligence
Copilot	Digital Literacy, Data Literacy, Programming and Coding, Cybersecurity, Cloud Computing, Artificial Intelligence and Machine Learning	Communication, Adaptability, Critical thinking, Teamwork, Emotional intelligence, Problem-Solving

Source: (Google Gemini, 2025; Microsoft Copilot, 2025)

A listing of Google's generative AI (Gemi) response and Microsoft's generative AI (Copilot) response to the query of technical and soft skills of the information decade is presented in Table 1. The items are colour-coded to highlight skills that were commonly identified by both AIs.

Applications of ML in Electrical Technology: Local

One may argue that before machine learning can become fully functional and applied in Nigeria's electrical and electronic sector, the foundations of power generation, transmission and distribution needs to be fully installed, functional and stable. However, ingenuity and dexterity are two critical factors amongst others that would determine the large-scale adoption of ML in Nigeria's electrical sector. The following are some case studies of how machine learning in being applied in Nigeria's electrical sector.

Energy Consumption Forecasting: The Long Short-Term Memory (LSTM) model was used by Edoka et al., (2023) to forecast the Short-Term consumption performance of the Transmission Company of Nigeria (TCN) 132/33KV transmission station Benin City. The purpose was to forecast short-term load for the case study. Energy consumption forecasting is an operation of predicting the future energy consumption of electrical systems using historical data. Edoka et al., (2023) employed Mean Absolute Percentage Error (MAPE) and Root Mean Square (RMS) to analyse the data. According to Edoka et al., (2023) the findings proved that LSTM model can be used to forecast short-term electrical load consumption with minimal error. LSTM is a deep learning model which is a subset of machine learning.

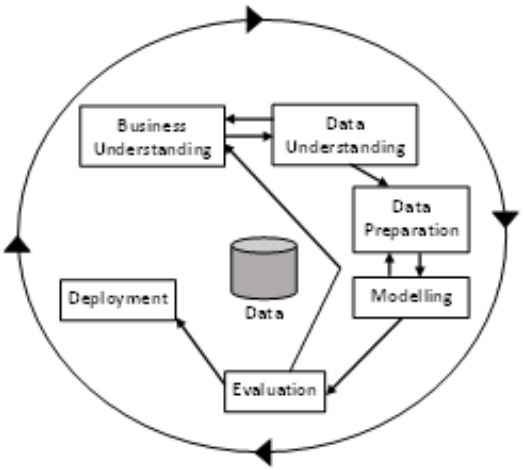

Figure 1: Cross-Industry Standard Process for Data Mining
Source: (Edoka et al., 2023)

Edoka et al. (2023) used the Cross-Industry Standard Process for Data Mining (CRISP-DM) method to gather and understand the dataset. This method entails six phases (see Figure 1) namely: Business understanding, Data understanding, Data preparation, modelling, Evaluation, and Deployment. According to Edoka et al. (2023), Business understanding entails comprehending the project's objectives, Data understanding refers to interacting with the source of the data in order to identify the data problem, Data preparation refers to data cleaning, transformation and reduction tasks, Modelling entails training a mathematical algorithm with the use of training data to become of capable of prediction, Evaluation refers to assessing the model's performance when tested with new dataset, and Deployment refers to

the actual use of the model for real-life situations. After choosing the method, Edoka et al. (2023) applied the LSTM architecture proposed by Le, Ho, Lee, and Jung (2019) using Jupyter Notebook, Python 3.7.7, Pandas, Seaborn, NumPy, and Keras (a deep learning python library). Thus, Seaborn served for data visualization, NumPy served for math and matrix operations, Pandas served for loading the data from the file directory, and Keras served for developing and evaluating the deep learning model based on Le, Ho, Lee, and Jung (2019) LSTM architecture. Using these tools, the model was built then trained. The model was trained on a five months records of the daily half-hourly load reading sheet from TCN Benin regional 132/33kV transmission station, which contained 3,672 data points. The model and data were analysed by charting the energy consumption for the five-month period, first 24-hour energy consumption, weekly consumption rate, and monthly consumption. While the model's performance was measured by comparing actual consumption in MW against predicted consumption in MW, and measuring the MAPE and RMS. Edoka et al. (2023) LSTM model showed a strong performance with MAPE and RMSE value of 0.010 percent and 19.79 respectively at 100 Epochs. Thus, the prediction is very impressive and the error minimal. Fuzzy Neural Networks, Gray Algorithm, and Gray Markov Model have also been used by other scholars for energy consumption forecasting (Omorogiuwa Eseosa & Ashiathah Ikposhi, 2021).

Machine Learning Applications: Other sectors

1. **Healthcare:** Nwachukwu (2024) tested the performance of three (3) ML models in predicting immunization completion rates using Primary Health Care Centres dataset based in Ogun State, Nigeria. The research objective was to produce immunization completion rate patterns with respect to features such as demography (child's age, child's gender), socioeconomics (maternal occupation, and family income level), and healthcare access (measured in kilometres from healthcare facilities). Such patterns could then be used to predict immunization completion rate based on strongly correlated features. Also, the pattern can be used to improve immunization healthcare intervention strategies. Logistic Regression (LR), K-Nearest Neighbour (KNN) and Support Vector Classification (SVC) were the three applied models. With 8,808 records, Nwachukwu (2024) used 80% for training and 20% for testing. By comparing the Accuracy, Mean Standard Error (MSE), and Absolute Mean Error (MAE), Nwachukwu (2024) found that Logistic Regression outperformed Support Vector Classification, and K-Nearest Neighbours. An unexpected pattern was revealed by the socioeconomic variable of family income level: children in high-income earning families had the least immunization completion rate compared to low-income and moderate-income families (Nwachukwu, 2024). This information would indeed be instructive in subsequent immunization programme strategies.

   In another study, Okunade, Ochigbo, Dada, Mikail, and Oyewande (2024) used ML to predict health insurance subscription. In this research, data was extracted from a three-year period Nigerian National Longitudinal Phone Survey (NLPS). The dataset was cleaned to remove null entries. By correlating the cleaned dataset,

Okunade et al., (2024) evaluated the association between their dependent and independent variables. They used four ML models to predict National Medical Insurance cover and these models include: Random Forest, Support Vector Classification, Logistic Regression and Decision Tree. With 18,119 records the dataset had 7 independent variables and one dependent variable (Insurance coverage). 60% of the data was used to train the ML algorithm, 20% was used to validate the trained model and the remaining 20% was used to test the trained model.

2. **Flood Prediction in Kebbi State**: Lawal, Yassin, and Zakari (2021) published their applied research on the performance of three (3) ML models in predicting the probability of flood occurrence in Kebbi State, Nigeria. By extracting 33 years of rainfall data from the Nigerian Meteorological agency (NiMet), Yelwa Kebbi State, they trained three models: Decision Tree (DT), Logistics Regression (LR) and Support Vector Classification (SVC). The performance comparison revealed that LR had higher accuracy score, and Recall Score than its two counterparts. Lawal et al. (2021) opined that the very poor performance of SVC model in their test was due small dataset. Preferably rainfall data covering 100 years would be ideal for better prediction performance (Lawal et al., 2021). However, they observed that despite the seeming small dataset, LR model performed admirably. To predict the probability of flood occurrence, Lawal et al. (2021) computed the average annual rainfall in Kebbi state and proposed that if the total yearly rainfall exceeds this average, then flood will probably occur, otherwise, it will not. This was indeed a bold and novel application. However, waiting to use the total yearly rainfall would not satisfy the purpose of the prediction: provide early warning to residents about a potential flood. Hence, the yearly calendar can be customized (like May 1981- April 1982, May 1982 – April 1983, etc.) and used to retrain the models and test for accuracy. This way, the prediction result would be ready by May of each year and residents can be notified of what to expect in the subsequent months.

3. **Construction Industry**: Loya, Eze, Awodele, Sofolahan, and Omoboye (2024) surveyed 143 construction practitioners in Nigeria. These practitioners comprised consultants, contractors and clients. The survey analyses revealed that ML is being applied in tasks like site works (wall painting, plastering), detection and classification of pavement stress, prediction of design energy of buildings, prediction of recycled concrete compressive strength and failure, construction workforce assessment and activity recognition, construction equipment assessment and activity recognition, prediction of heavy equipment parameters, building occupancy modelling and performance simulation, and building lifecycle assessment and management. For these nine ML tasks there was no significant variance in the group's level of awareness. Out of these nine application areas, the construction practitioners further affirmed their organization's readiness to adopt ML in three (3) application areas namely: prediction of the energy system behaviour of buildings, construction workforce assessment and activity recognition, and construction equipment assessment and activity recognition. The practitioner-groups varied significantly in their opinion

about their organisation's readiness to adopt the other six ML application areas that they are aware of. Nonetheless, practitioner-groups did not vary significantly concerning readiness to adopt three (3) other ML application areas in which they had varied significantly concerning level of awareness. These areas include: Structural health monitoring and prediction, Schedule management, and 3D model's classification in BIM. Despite the significant variance amongst the construction-groups about their awareness of certain ML application areas, all application areas in both surveys had a mean-score between 3.29 - 4.41. Therefore, there is a high level of awareness of and readiness to adopt ML in Nigeria's construction industry.

Machine Learning Applications in Electrical Technology: International

1. **Electrical Infrastructure Inspection**: Constellation Clearsight (a subsidiary of Constellation Energy Corporation) partnered with Microsoft Azure and Azure AutoML to rebuild its electrical system distribution infrastructure inspection technology. This technology provides innovative technology solutions, drones, robots, and sensors that provide business intelligence in the inspection of electrical system distribution infrastructures.

   Clearsight's solution entailed automating the process of capturing pictures of electrical distribution systems, and analysing the data to provide business intelligence that enhances inspection safety, efficiency, and quality of electrical system visual inspection. Hence, Clearsight applied a part of Machine Learning known as computer vision to deliver this solution. To achieve this, they needed machine learning platforms and tools, and Microsoft Azure and Azure AutoML proved to be their reliable and efficient option. With Azure they were able to store captured images, and with Azure AutoML they were able to build, train their models and build test pipelines. This integrated platform for Machine Learning applications proved to be more effective and beneficial than Clearsight's previous approach (BalaB, 2022). Overall, Azure Machine Learning support for computer vision tasks enabled Clearsight to rebuild a more efficient and easier to use inspection model; Azure's Machine Learning data labelling and AutoML for images significantly reduced the build and deployment time for Clearsight's new computer vision models by 50% (BalaB, 2022). Jupyter Notebook was also used in the end-to-end workflow of Azure Machine Learning solution.

2. **Predictive Maintenance**: Machine Learning algorithms are being employed to predict potential failures, monitor engine health, and schedule proactive maintenance for electrical equipment and power system networks. This approach integrates cutting-edge computing and advanced ML techniques to facilitate maintenance strategies and reduce downtime. For example, General Electric Aviation provides "Prognostic Health Management Plus" for its CF34-3 engines and enjoys patronage from 200 operators in 70 countries (GE Aerospace, 2016);

Schneider Electric (an electrification, automation and digitisation firm) provides predictive maintenance solutions that help reduce electrical equipment downtime and improve workplace safety. The firm has its dedicated machine learning technologies that digitize and visualize operational management, provide real-time control of maintenance, provide visualization of energy usage, and provide insights to reduce energy and operational cost (Schenider Electric, n.d.). Rio Tinto (a metals and mining corporation) deploys sensors and predictive analytics software to mining facilities and processes. According to AIX (2024), the company's predictive maintenance model provides a seven-week advance notice for necessary maintenance thus reducing operational costs, and minimizing disruptions. To achieve this, Rio Tinto partners with Amazon Web Service (AWS).

Machine Learning Competencies Development

Machine Learning is a contemporary skill, it is a competency worth developing, and it is the competency of the future. Start from a bedroom to a kitchen, and from a sitting room to a balcony, you will find machines, machines performing repetitive tasks whose information we can use to improve the quality of daily life. But that data cannot be extracted effectively and utilized without the appropriate competence – Machine Learning Competencies. The same applies at the faculty levels within an academic institution: if the research products of each department can be collated to a central platform, useful metrics can be identified, and innovative collaborations would emerge.

Methodology

The busy and competitive schedule of technological practitioners makes it difficult for them to publish academic articles about their latest innovation. However, their comments about their product, or exhibition of their product and services, or their review of similar technologies can be found in the dailies, blogs, corporate websites, or mentioned in journal articles. Hence, responding to a survey can be one of the effective ways to receive feedback and focused comments from them. In this information age, these dailies, blogs, corporate websites and journal articles are spread across the internet to which search engines and generative AI have access to. Thus, keywords were used to query two generative AIs (Gemini and Copilot) and two search engines (Google search and Google Scholar). Each query result was filtered by relevance to research topic, then all four filtered results compared to select common items. For each selected item, references and citations were visited to determine the context and accuracy of interpretation.

Out of the over twelve (12) technological skillsets (technical and soft skills), the selection was narrowed to machine learning, and case study applications of machine learning in electrical technology were investigated focusing on both local and international published facts. Machine Learning was chosen for to its alignment with electrical and electronic technology. Moreover, its competence builds on several other technical skills.

Data Presentation and Discussion of Findings

Common Machine Learning algorithm, tools, programming languages, use-cases are presented in Tables 2-4.

Findings

1) Tools, and algorithms needed to develop Machine Learning Competency are accessible, and they are already being used in Nigeria. Some of such common tools are listed in Table 2, while such common ML algorithms are listed in Table 3, and some common applications of listed in Table4.
2) Globally competitive companies have machine learning operations integrated into their products, services and operations.
3) Machine Learning operations require datasets, computing languages like Keras or Pandas, storage technologies like MongoDB or PostgreSQL, data cleaning, data analysis, and subject experts to interpret the acquired datasets.
4) Machine Learning finds applications in electrical technology just like it finds application in Healthcare, Minning, Flood control, Construction, and economic analysis amongst many others.
5) Electrical technology and electronic technology course contents and teaching facilities need to be modified appropriately in order to equip her students and researchers with Machine Learning competencies before graduation. This competence finds applications across all spheres of human endeavour. Provided data is being generated, Machine Learning can be used to optimize business operations.
6) Machine Learning does not replace people at the workplace rather, it optimizes the performance of repetitive tasks so that the available human capital can process more complex data and social problems.
7) The appropriate use of Machine Leaning in the construction industry, immunization strategies, healthcare insurance cover, electrical equipment inspection, electrical equipment maintenance scheduling, all demonstrates that Machine Learning enhances workplace productivity.

Table 2: Some Machine Learning Use-Case

S/N	Use-Case
1	Energy Consumption forecasting
2	Electrical Infrastructure Inspection
3	Predictive Maintenance
4	Digital Transformation
5	Energy usage visualization
6	Energy cost visualization and operational cost visualization
7	Transmission line fault detection
8	Transmission line fault prediction
9	Immunization Completion Rate
10	Prediction of Health Insurance Completion
11	Flood prediction
12	Construction site works (wall painting, plastering)
13	Pavement stress detection and classification
14	buildings design energy prediction
15	recycled concrete compressive strength and failure prediction
16	construction workforce assessment and activity recognition
17	construction equipment assessment and activity recognition
18	heavy equipment parameters prediction
19	building occupancy modelling and performance simulation
20	building lifecycle assessment and management.

Table 3: Common Machine Learning Tools and Languages

S/N	Tools	Languages
1	Jupyter Notebook	Python
2	Keras	Python
3	Pandas DataFrame	Python
4	NumPy	Python
5	Microsoft Azure	
6	Amazon Web Service	
7	MongoDB	
8	PostgreSQL	
9	TensorFlow	
10	PyTorch	Python
11	Scikit-learn	Python

Table 4: Common Machine Learning Algorithms

S/N	**Algorithms**
1	Logistic Regression
2	K-Nearest Neighbour
3	Support-Vector Classification
4	Random Forest
5	Decision Tree
6	Fuzzy Neural Networks
7	Gray Algorithm

Conclusion

The technological demands of this decade and century emphasises data literacy. This can be achieved under an instructor-led study or self-study. Tools, and algorithms needed to develop Machine Learning Competency are accessible, and they are already being used in Nigeria. Hence, students and researchers should equip themselves to positively transform their institution, community, and nation.

Recommendation

A combination of instructor-led and self-study needs be used to develop Machine Learning competencies. If learners can be introduced to computational thinking during their primary and secondary education, they would be better equipped to productively perform Machine Learning research during their college or University programme.

Contribution to Knowledge

1) Suggests an alternative strategy to compute the average annual rainfall needed to train ML models to predict the risk of flood occurrence.
2) Demonstrates the need for programming, and computational thinking subjects in primary and secondary education prior to College and University programmes. This way, students would have the prerequisite knowledge needed to productively perform ML research.
3) Highlights some contemporary and replicable professional use-case of ML.

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