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Development of Artificial Intelligent Based Model for Improving Productivity and Reducing Manufacturing Cost

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Abstract

This study proposes an artificial intelligence-driven model that can enhance productivity and reduce manufacturing costs in the brewery industry of Nigeria. The research initiated with a critical literature review on the factors of productivity in the knowledge-intensive industries, choosing thereupon the brewery sector based on expert advice. In total, three predictive models were developed, namely Artificial Neural Network, Machine Learning, and a hybrid Artificial Neural Network-Machine Learning model, for predicting productivity. The Mean Squared Error was 0.001399 for the Artificial Neural Network model, Root Mean Squared Error was 0.037407, and Mean Absolute Error was 0.037283, while the Machine Learning had Mean Squared Error of 0.040378, Root Mean Squared Error of 0.200943, and Mean Absolute Error of 0.183000, the hybrid having Mean Squared Error of 0.013982, Root Mean Squared Error of 0.118247, and Mean Absolute Error of 0.110141. It also proved the fact that the Machine Learning model is able to predict productivity based on maintenance, Mean Time Before Failure, and Mean Time to Repair indicators since the obtained values for this type of model had lower errors than all the others: Mean Absolute Error = 0.08508, Mean Squared Error = 0.19275, Root Mean Squared Error = 0.43903.

Keywords: Artificial Neural Network, Machine Learning, Productivity, Manufacturing Cost, Artificial Intelligence.

1. INTRODUCTION

The emergence of Industry 4.0 has brought about significant changes in the manufacturing sector, with a focus on data-driven decision-making and the use of artificial intelligence (AI) and machine learning (ML) algorithms to optimize production processes. The development of Artificial Intelligent (AI) model is one of the most important events in recent human history. Human activity has long become the most defining influence on our global ecosystem. The pace of change has rapidly accelerated in the last 250 years since the invention of the steam engine and the resulting first industrial revolution (Muller, 2014). AI systems are designed to enabling computers to perform tasks like perceiving, reasoning, and problem-solving (Chui *et al.*, 2018).

Artificial intelligence (AI) is a collection of approaches and techniques designed to enable computers, particularly computer systems, to mimic human cognitive processes. A subset of artificial intelligence known as machine learning (ML) offers a number of approaches and tactics that enable systems to be improved. Automatic learning processes, which produce knowledge from prior experiences (data), are the foundation of machine learning. Massive process monitoring data, made possible by the cyber-physical systems (CPS) spread along the production processes, is one of the major components of this next industrial revolution and the undisruptive capabilities that AI and ML bring.

The manufacturing sector is facing increasing pressure to improve productivity and reduce costs. The use of AI-based models has the potential to address these challenges by optimizing production processes, predicting maintenance needs, and improving product quality. Also, the chance to enhance the performance of manufacturing processes is by incorporating those new information streams, applying analytical techniques, developing new supporting models, tools, and services, and comparing their suggestions and results to conventional methods. However, there is a need for further research on the development of AI-based models for manufacturing applications. The application of AI algorithms has the potential to significantly improve productivity and reduce manufacturing costs.

The increasing manufacturing cost is a significant problem in brewery industries, negatively impacting profitability, competitiveness and ability to invest in growth and innovation. The rising cost of energy, maintenance of equipment and overheads are squeezing the brewery industries. The challenges have also affected product quality, pricing strategy, and distribution of product (supply). If ignored, the escalating manufacturing cost will threaten our business sustainability, hinder our expansion plans, and compromise our commitment to delivering high-quality products to our customers.

Furthermore, the lack of real-time data and analytics is making it difficult to identify areas for improvement, optimization of production schedules and make informed decisions. Low productivity is a persistent problem in brewery industries, hindering ability to meet growing demand, reduce costs, and improve overall efficiency. Inefficient processes, inadequate equipment, and insufficient training are resulting in wasted resources, delayed production and inconsistent product quality. Failure to address these issues, the productivity problem will continue to erode our competitiveness, compromise our customer satisfaction, and limit our growth potential (Castellani *et al*., 2019).

Unplanned machine failures and inadequate maintenance of manufacturing equipment are also major problems in brewery industries, resulting in costly downtime, reduced productivity, and compromised product quality. The frequency and severity of equipment failures are disrupting production schedules, leading to missed deliveries, and impacting the ability to meet customer demand. Similarly, the lack of preventive maintenance, inadequate spare parts inventory, and insufficient training of maintenance personnel are exacerbating the problem, leading to prolonged downtime, increased repair costs, and decreased equipment lifespan. If left unaddressed, the machine failure and maintenance problem will continue to erode our operational efficiency, compromise our customer satisfaction, and impact our bottom line (Brynjolfsson *et al*., 2019).

Despite the potential benefits of AI-based models in manufacturing, there is a lack of research on the development and implementation of these models in real-world manufacturing settings. This study aims to address this research gap by developing and evaluating the performance of an AI-based model for predicting and enhancing productivity in a manufacturing setting. Productivity has become a versatile word as by and large everyone talks about it. The meaning of "productivity" is different for different people. Consequently, it varies from efficiency to effectiveness. Productivity is a measure of the efficiency with which a company or an enterprise converts its available resources (inputs) into finished goods or services i.e. required outputs. Measurement of productivity commonly supposed to be a ratio of outputs produced to resources consumed (Card, 2006). The ratio of output quantity index to the input quantity index is the measuring tool for productivity change (Balk, 2005) thus, a total productivity measure reflects combined impact of all the inputs in producing the output. To measure productivity for multiproduct firms, productivity can be enhanced by producing more output with the same input or by producing the same output with fewer inputs. Productivity can be defined as human efforts to produce more and more with less and less inputs of resources as a result of which the production benefits are distributed among maximum number of people (Inkpen, 2005).

Meeting quality and machine maintenance while guaranteeing productivity improvement were the primary driving forces and criteria in the majority of everyday manufacturing operations across sectors (Wang *et al*., 2019). Meeting these has grown more challenging because of the numerous demands brought on by the complexity of products and processes, the fluctuation of client demand and preferences, and the constant push from rival businesses to maintain their profitability has grossly affected productivity. Positively, this challenging business environment for most firms offers a chance for the distinctive advantages of AI above traditional tools and methods. Particularly, the routine task of problem-solving, which entails seeking out underlying causes, is ideally suited for AI tools that are capable of seeing and categorizing multivariate, nonlinear patterns in operational and performance data that are obscure to the plant engineer (Zhao *et al*., 2019).

Machines, environmental sensors, controllers, labor records, etc. produce enormous volumes of continually generated data nowadays. These categories might be used to group the data: (1) Machine availability, uptime, reliability, and downtime data (2) Process information gathered from sensors on process equipment or stations, such as coolant temperatures for machining and grinding, power, and heat treat temperature/energy, (3) Information on production operations captured by controller systems, such as timestamps or the amount of time each component spent in each station of operation, machine downtime, starvation/blockage, idle time, and shift scheduling, (4) data derived from measurements or checks made during product quality inspections, such as product diameter, shape, and balance (Liu *et al*., 2018). All of these include previously unheard-of potential for pattern discovery that may provide crucial hints for resolving challenging issues while providing a complementary knowledge of the physical significance of parameters to other physical aspects of a system or process (Wang *et al*., 2018). In addition to having the capacity to interpret highly dimensional data, AI also has the capacity to translate the vast quantities of complicated industrial data that are now routinely generated in modern factories into useful and insightful information (Sharp *et al*., 2018).

Damioli *et al*., (2021) studied on how artificial intelligence affected worker productivity. The research demonstrated that, even adjusting for other patent-related activity, AI patent applications had a particularly beneficial impact on businesses' labor productivity. The effect mostly affects SMEs and the services sector, indicating that one of the key factors influencing the impact of AI so far identified is the capacity to swiftly adapt and implement AI-based applications in the production process. Artificial intelligence and robotics (AI) patenting activity appears to have increased in recent years, which suggest that products based on AI technology may have begun to have an impact on the economy. Using a sample of 5257 businesses from across the world that between 2000 and 2016 submitted at least one patent in the field of artificial intelligence, we test this assertion.

Shahin *et al*., (2004) researched on Applications of Artificial Neural Networks in Foundation Engineering. The objective of this study was to highlight the use of ANNs in foundation engineering. The study also described ANN techniques and some of their applications in shallow and deep foundations, as well as the salient features associated with ANN model development. Finally, the paper discussed the strengths and limitations of ANNs compared with other modeling approaches and have emerged as one of the potentially most successful modeling approaches in engineering. In particular, ANNs were applied to many areas of geotechnical engineering and have demonstrated considerable success.

Mohammed *et al*., (2020) evaluated a collection of machine learning models with the goal of assessing productivity loss brought on by change orders. According to the kind of work, its effect, the quantity of change orders, their frequency, the average size of change orders, and the number of hours associated with change orders, the loss of productivity were assessed in the proposed model. The machine learning models that were used included the generalized regression neural network, the cascade forward neural network, the Elman neural network, the back propagation neural network, the multiple linear regression, and the hybrid particle swarm optimization-linear regression. It was demonstrated that radial basis neural network outperformed other machine learning models, with mean absolute percentage error, mean absolute error, and root mean square error, respectively, of 2.44%, 0.014, and 0.027.

Awodele and Jegede (2009) researched on Neural Networks and Its Application in Engineering. The purpose of this study was to examine neural networks and the various architectures of NN and the learning process. The needs for neural networks, training of neural networks, and important algorithms used in realizing neural networks have also been briefly discussed. Neural network application in control engineering has been extensively discussed, whereas its applications in electrical, civil and agricultural engineering were also examined. They concluded by identifying limitations, recent advances and promising future research directions.

Singh *et al*., (2022) researched on development of artificial intelligence-based neural network prediction model for responses of additive manufactured polylactic acid parts. Fused deposition modeling (FDM) is one of the most economical and popular technology amongst numerous additive manufacturing techniques. The quality of FDM fabricated parts is highly sensitive to the production parameters. Thus, in the work, an investigation on the FDM printed polylactic acid parts has been performed considering six printing process parameters, that is, nozzle diameter, build orientation, raster pattern, layer height and print speed to develop the feedforward backpropagation (FFBP) artificial neural network prediction model for the prediction of responses, namely, tensile strength, material consumption, build time and surface quality.

Tensile specimens as per L_{27} orthogonal array are printed considering the various combination of parameters. The printed samples have been subjected to tensile strength testing, surface roughness measurement, build time recording, and material consumption evaluation. The highest tensile strength of 57.633 MPa, lowest surface roughness of 1.71 µm, lowest build time of 0.35 h and lowest material consumption of 7.8 g are observed. The experimental results have been used to develop the artificial intelligence-based prediction model through FFBP algorithm and sigmoid transfer function to predict the responses. The best performance of the developed neural network with R^2 for testing (0.99343), training (0.99366), and validation (0.99372) of data is recorded for prediction of responses with minimum percentage error. The study concluded that developed model is capable of predicting the responses of FDM process according to the input process parameters.

Kumar *et al*., (2024) researched on artificial intelligence and intelligent factories for the future. This chapter explores the future of artificial intelligence (AI) in the context of intelligent factories. It delves into the transformative potential of AI technologies in revolutionising manufacturing processes, optimising production, and creating highly efficient and adaptive factory environments. The work discussed the key components of intelligent factories, including AI-powered automation, machine learning algorithms, and the integration of the Internet of Things (IoT) and big data analytics. It explores how these technologies work together to enhance productivity, quality control, and responsiveness in manufacturing operations. This chapter emphasises the need for a holistic approach, considering the technical, economic, and societal implications of AI implementation in factories. The future of AI and intelligent factories is one of collaboration and augmentation, where human expertise and creativity intersect with AI capabilities to drive the next wave of the industrial revolution.

Wang *et al*., (2023) researched on the impact of artificial intelligence on total factor productivity: empirical evidence from China's manufacturing enterprises. Using the panel data of 938 listed manufacturing companies in China from 2011 to 2020, the work scientifically examined the impact of artificial intelligence (AI) on total factor productivity (TFP) of China's manufacturing enterprises by using the fixed effect model, mediating effect model and difference-in-differences model. The results showed that AI can significantly improve the TFP of China's manufacturing enterprises, as confirmed by a series of robustness tests. Technological innovation, human capital optimization and market matching improvement have proved to be three important channels for AI to affect the TFP of China's manufacturing enterprises. The impact of AI on TFP varies greatly among China's manufacturing enterprises in different geographical locations, industry characteristics, ownership and life cycle stages. The findings of this paper can provide theoretical insights and empirical evidence at the micro enterprise level for policymakers to give full play to the role of AI in promoting the high-quality development of China's manufacturing industry.

2. MATERIAL AND METHODS

The quest to improving work productivity in the sectors of knowledge-intensive industry has been a subject of academic and practical interest over the years. It has been noted that the conventional productivity systems of productivity mainly targeted one of the productivity dimensions of the task, employee, or organizational levels. However, all these factors are mutual and reciprocate their effects within the system to determine overall productivity. As to this complexity, one must consider the levels of analysis that should be integrated to form a comprehensive and accurate predictive model. In this regard, the current study has designed a theoretical ANNs-ML model that integrates task-level, employee-level, and organizational-level variables.

This proposed model consisting of ANN and ML methodologies will help establish a comprehensive framework that can accurately predict and enhance productivity based on its ability to handle non-linear relationships like ANN and its flexibility in managing various types of data and structures like ML. The following methodological framework is intended to overcome the complexity associated with the consolidation of multi-level factors and to ensure operational predictive capacity.

(i) Data Collection: In developing the algorithm for the study, data were compiled and harmonize from various sources, representing task-level, employee-level, and organizational-level factors:

a) Task-level data: Task characteristics (complexity, autonomy, feedback) and Task completion time and quality.
b) Employee-level data: Demographics (age, gender, education), Personality traits (Big Five) and Cognitive abilities (problem-solving, memory).
c) Organizational-level data: Organizational culture (innovation, collaboration), Leadership style (transformational, transactional) and Human resource management practices (training, feedback).

(ii) Data Preprocessing: in the processing of the data, the following operations were carried out:

a) Feature scaling which involves the standardization (z-scoring) and normalization (min-max scaling) of the data using Equations (3.1) and (3.2).

$$X_{std} = \frac{(X-\mu)}{\sigma} \quad (1)$$

$$X_{norm} = \frac{(X-X_{min})}{(X_{max}-X_{min})} \quad (2)$$

b) Handling missing values, this involves the imputation (mean, median, or regression-based) of the data using Equation (3).

$$X_{imputed} = \beta_0 + \beta_1 X_{related} + \varepsilon \quad (3)$$

(iii) Data transformation, this involves the Log transformation for skewed data, the expression is as in Equation (4).

$$X_{log} = Log(X) \quad (4)$$

2.1 ANN Model Development

The development of the model involves the training of the hybrid ANN-ML model to learn the intricate relationships between the multi-level factors and productivity outcomes and for the ANN it used the following features:

(a) An input layer of 15 neurons can be expressed as in Equation (5).

$$X = [X_1, X_2, X_3, \dots, X_{15}] \quad (5)$$

(b) Hidden Layer can be expressed as in Equations (5) and (7).

Layer 1: sigmoid activation function

$$h_1 = \sigma(w_1 X + b_1) \quad (6)$$

Layer 2: ReLU activation function

$$h_2 = ReLU(w_2 h_1 + b_2) \quad (7)$$

Output Layer (1 neuron): Productivity score (0-100%) as in Equation (8).

$$y = \sigma(w_3 h_2 + b_3) \quad (8)$$

Where, X is a 2-dimensional input vector, h is a 2-dimensional hidden layer vector, w_1 is a [1X2] matrix of weights between the input layer and the hidden layer,

b_2 is a 2-dimensional bias vector for the hidden layer, b_1 is a vector bias value for input layer, w_2 is a [2X2] matrix of weights between the hidden layer and the output layer, b_3 is a scalar bias value for the output layer, σ is the sigmoid activation function, w_3 is a [2 X 1] matrix for the last (output) layer and ReLU is the Rectified Linear Unit.

2.2 ML Model Development

For the ML Model development on the other hand, the following features are introduced:

a) Ensemble learning which a Gradient Boosting Machine (GBM) with 5-fold cross-validation as expressed in Equation (9).

$$y_{GB} = \sum (h_i(x) \text{ x } \gamma_i) \ (9)$$

b) Feature engineering and this involves the interaction terms, polynomial transformations, and clustering-based feature extraction and it is expressed as Equations (10), (11) and (12).

$$X_{interact} = (X_1 \text{ x } X_2) \ (10)$$

$$X_{poly} = X^2 \ (11)$$

$$X_{cluster} = Cluster\ (x) \ (12)$$

c) Hyperparameter tuning and this involves the Grid search and random search as given in Equation (13).

$$GBM_{hyper} = optimize(GBM(x, y), hyperparams) \ (13)$$

2.3 Hybrid ANN-ML Model Development

For the Hybrid Model which is based on ANN-ML hybrid, the study uses ANN output as input features for the ML model as in Equation (14).

$$y_{hybrid} = y_{ANN} + y_{ML} \ (14)$$

In the weighted voting, the study combined the ANN and ML model predictions using weighted voting (e.g., 70% ANN, 30% ML) as in Equation (2.15).

$$y_{hybrid} = 0.7 \text{ x } y_{ANN} + 0.3 \text{ x } y_{ML} \ (15)$$

Where, y_{ANN} is the output of the ANN model and y_{ML} is the input ML model.

The following evaluation metrics were used in this study:

(i) Mean Squared Error (MSE)

$$MSE = \frac{1}{n} \text{ x } \sum \left(y_{true} - y_{pred}\right)^2 \ (16)$$

(ii) Mean Absolute Error (MAE)

$$MAE = \frac{1}{n} \text{ x } \sum \left|y_{true} - y_{pred}\right| \ (17)$$

(iii) R-Squared (R)

$$R^2 = 1 - \left(\frac{MSE}{var(y_{true})}\right) \ (18)$$

(iv) F1-score (for classification tasks)

$$F1 = 2 \text{ x } \left(\frac{precision \text{ x } recall}{precision + recall}\right) \ (19)$$

This model includes equations for data preprocessing of the ANN and ML model development, and hybrid model development.

3. RESULTS AND DISCUSSION

The implementation of predictive and process efficiency with the use of Artificial Neural Networks (ANN) and other machine learning (ML) models has been found to be very advantageous in different fields. This work was aimed at analyzing the effectiveness of the chosen ANN model for predicting and enhancing the productivity of a brewery company. The findings thus revealed the superiority of the proposed ANN model over the classical ML models and a hybrid model in terms of predictive accuracy and computational performance gains. ANN model performance produced the following results, MSE (Mean Squared Error): 0.001399, RMSE (Root Mean Squared Error): 0.037407 and MAE (Mean Absolute Error): 0.037283.

The results of the ANN model showed an excellent performance with extremely low error rate in all the parameters. The MSE is the mean or average of the squared difference between the projected and actual values. The nearly zero value of MSE signifies that the actual values closely resemble those predicted by the ANN model, which means that the model is highly accurate. The RMSE gives a measure of the size of the prediction errors. The low RMSE value again emphasizes on the fact that there is less variability from the actual values and the MAE measures the average size of the error of estimates for some given set of predictions without paying attention to the sign of errors. The low value of MAE indicates that the predicted values of the model are always near the actual values. Figure 3.1 shows a display of the performance of the ANN model and it clearly indicates a high degree of accuracy and precision. The low error values indicate that the ANN model could accurately predict the productivity of the brewery company and may therefore be useful for the purpose of predictive maintenance and the improvement of the company's business processes.

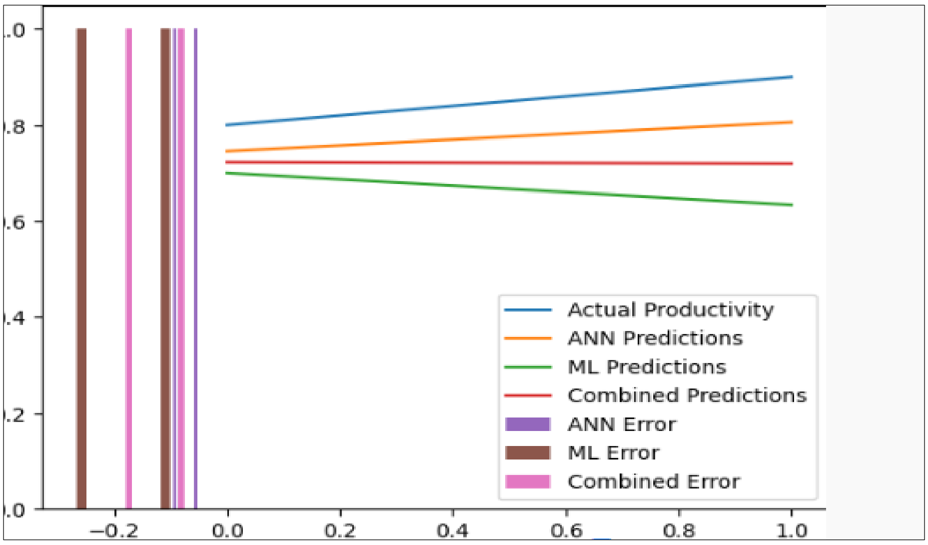

Figure 1: Graphical Display of the Performance of the Models.

Similarly, the performance of the ML Model includes, MSE values of 0.040378 (moderate), RMSE values is 0.200943 (moderate) while the MAE value is 0.183000 (moderate). As for the traditional ML model, while being rather proficient, possesses comparatively more prominent error rate than the specified ANN model. It can be observed that MSE of the ML model is much greater than that of the ANN model suggesting that the predicted values of the ML model are less precise. This is supporting the fact that RMSE value is higher, which implies higher deviation from actual value and therefore may hinder the dependability of the forecasts under a real production setting. The MAE is also higher, meaning this is a larger average prediction error than in the case of the ANN model. However, these error metrics indicate that the ML model provide sufficiently low prediction errors for many practical purposes. But this leads to relatively high error values which show that there is potential for further improvement than that seen in the ANN model.

The hybrid or Combined model performance, the MSE value was found to be 0.013982, The RMSE value was 0.118247 while the MAE value is 0.110141. Integrating elements from the supposed ANN model and traditional ML models leads to enhanced performance indices. The MSE is low, meaning that the average of the squared difference between the observed data and the predicted values is quite low and improved when the two models are combined relative to the standalone ML model. RMSE is also calculated and is lesser than the previous model implying that there is less deviation from the actual measurements and the values of MAE are also nearer to that of ANN model which depicts here that the combined model gives a high level of accuracy to the predictions made by it. The availability and assessment of the proposed comprehensive model's performance criterion set reveal that it provides an excellent synergy of ANN as well as the ML traditional model. The error values depict that the proposed integration method can also achieve a better prediction same as that of ANN model while reducing the errors encountered in standalone ML model. From this it can be concluded, that the use of hybrid models can be used as quite reasonable approach towards improving prediction accuracy and reliability for application in industrial settings.

Therefore, based on the analysis of the results achieved in this study, one can conclude that the proposed models for productivity increase have been effectively applied by the brewery company. One of these is ANN model, which, for example, shows very low error metric and can be used effectively for predictive maintenance and improving the processes. Such accuracy enhances organization and automatically reduces downtime and helps optimize maintenance schedules thus improving productivity. Also, when comparing the models, it is apparent that the performance of the ANN model is exceptionally good indicated by extremely small values of MSE, RMSE, and MAE. The more established ML model as shown above has high error measures meaning less accuracy.

Despite the fact that the combined model gives a balanced approach, it is important therefore to get appreciable performance indicators, which is closer to the models, such indicates that can be integrated into the models and can lead to improvement of the predictive capability. In terms of management, operational performance and the physical improvement of the productivity of the company, these indicators are integrated into the model algorithm (code) some of the indicators considered include, time (hours), failures, repairs rate or times (hours), production rate (units/hour), MTBF and MTTR. With this, the study was able to help in the management of the maintenance activities in an effective manner to prevent failures that can be attributed to the equipment. This type of maintenance efforts as a proactive maintenance strategy enables the smooth and continuous operations, high facility throughput capacity as well as high efficiency in the brewery business. In a nutshell, the findings which are shown in Figure 4.2 confirm the usefulness of more elaborate analytical techniques, especially ANN, in augmenting the efficiency and accuracy of brewing processes. Thus, utilizing these models, the brewery would be able to optimize its operations, adhere to high manufacturing standards, and schedule equipment maintenance in timely and efficient manner and, therefore, enhance its overall business performance.

Figure 2 depicts the predicted production rate of the brewery equipment and company following successful validation of three models, including the ANN, ML and Combined. The study can clearly observe that all the three models predicted a higher production rate in relative to the actual production rate in the simulated period. This indicates that the models provide the brewing company with areas of focus that can help it increase the brewing volume. While all of the models presented above seem to underestimate the real picture, the combined model only seems to give the highest level of production rate over the entire time period. This means that by combining the two models, the achievable production rate is predicted with a higher level of accuracy compared to when the ANN and ML models are used individually.

Similarly, Figure 3, shows the evolution of the MTBF and MTTR parameters in relation to a piece of brewery equipment considered is presented. Looking at the MTBF line in the graph, it could be observed that it is more or less constant which means the average time between failures for this kind of equipment has not changed significantly over time. This is a positive pointer that the equipment is running with the least of faults and breakdowns. Despite this, it can be seen that the MTTR line is gradually decreasing over the period of time. In an MTTR graph, it would be desirable for the line to slope downwards as this would mean that time taken in repairing the equipment after a failure is decreasing. This however, could be due to:

i. Improved maintenance procedures: The workers or mechanics or technicians who are carrying out the repairs probably work much faster now in terms of identifying the root cause of the failure and repair time.
ii. Spare parts inventory optimization: The brewery may also have streamlined its stock of spare parts in a way that guarantees the availability of the appropriate spare parts once a repair is required, and in such a way that will not disrupt the business operations significantly.
iii. Standardized repairs: The repeated incidents may have prompted frameworks for expected repair work and the way maintenance staff can handle them in a quicker and more effective fashion.

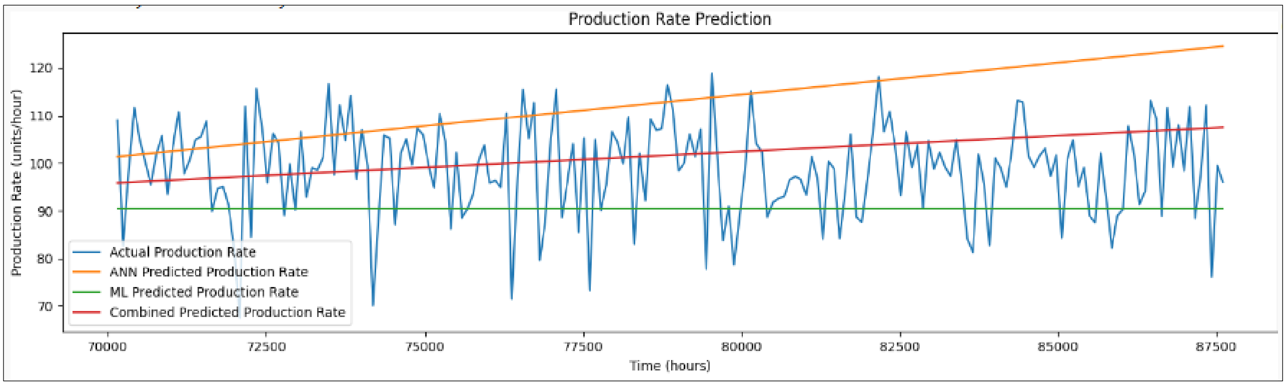

Figure 2: Predicted Production Rate of the Brewery Equipment and Company

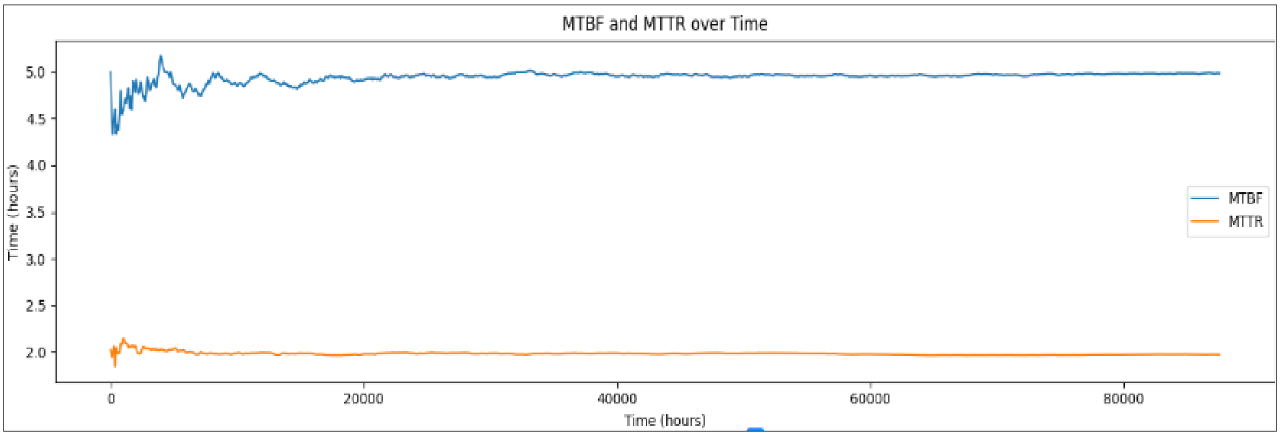

Figure 3: MTBF and MTTR Parameters in Relation to the Brewery Equipment.

Furthermore, Figure 4 shows a line graph that compares the predicted productivity of a brewery company using three different models: ANN, ML, and their Combination. In the figure, it is not hard to see that the x-axis denotes the sample number while the y-axis denotes the productivity. The actual productivity is shown as blue colored line, the ANN predicted productivity as green colored line, ML predicted productivity as red colored line, and the combined productivity is shown as purple colored line.

From the graph, it can be seen that the productivity levels predicted by the ML model were at its highest levels, followed by the combined model and then the ANN model. The actual productivity is less than that predicted by the ANN but more than that of the combined model for most of the samples. As for the model assessment, it can be seen that the chosen ML model has the highest performance according to the metrics provided. It has the lowest MAE of 0.08508 meaning that the average difference between the predicted values and the actual values was the least. It also has the least MSE of 0.19275 and RMSE of 0.43903 which means that the squared deviations between the predicted values and the actual values were on average the least. The ANN model, on the other hand, has higher errors compared to the other two models. It has a MAE of 0.74491, MSE of 0.94987 and RMSE of 0.97461. The MAE for the combined model is 0.39186, MSE of 0.28260 and RMSE of 0.53160 which are lower than the ANN model but higher than the ML model. In conclusion, the performance metrics seem to suggest that the ML model is the best choice for making productivity predictions in this particular scenario.

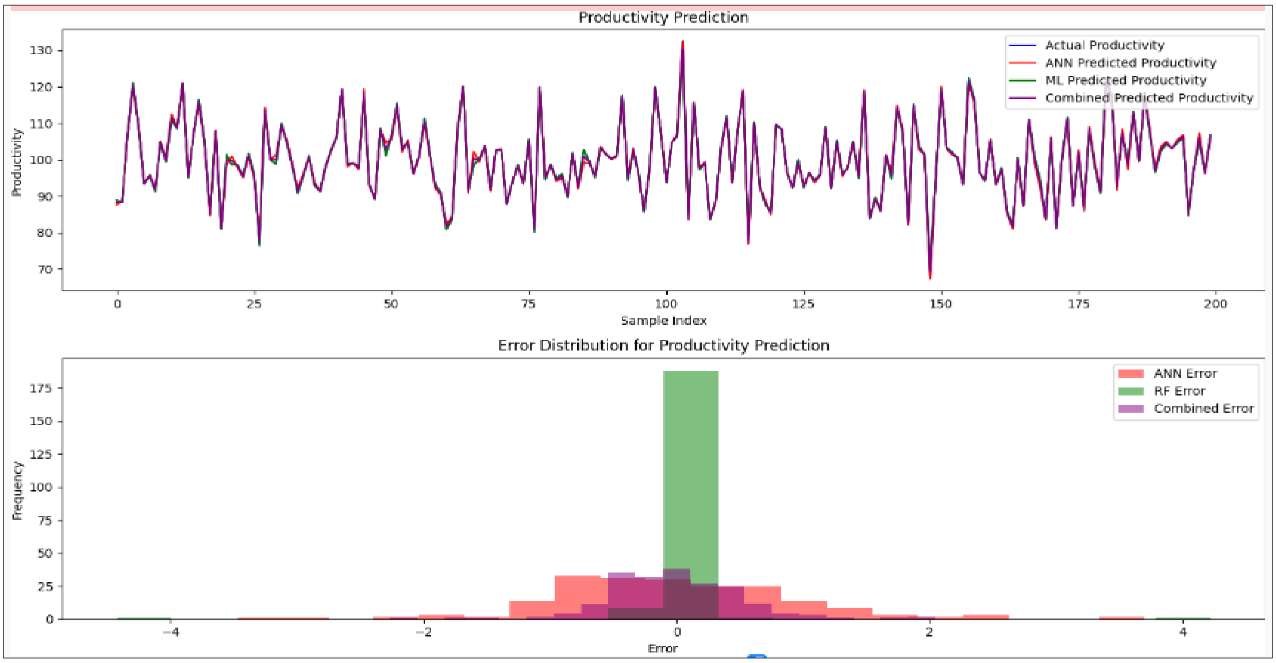

Figure 4: Results Comparing the Productivity Prediction and Error Distribution Productivity Prediction.

4. CONCLUSION

With the successful completion of the research study that aimed at developing an artificial intelligent–based model for improving productivity and reducing manufacturing cost, the following concluding remarks can be drawn from the study:

i. Comprehensive Investigation:

The study commenced by systematically reviewing the specific task, employee and organizational factors influencing productivity in knowledge intensive industries in Nigeria. This study was crucial in choosing the particular industry to focus on for the study. At the end, the brewery industry was selected based on expertise advice from scholars.

ii. Development of Intelligent Models:

The following three models were designed to predict productivity in brewery industry: ANN, ML and ANN-ML. This research showed that the ANN model offered better predictive accuracy and computational efficiency than the classical ML and hybrid models.

iii. Model Performance Metrics:

The ANN model gave an MSE of 0.001399, RMSE: 0.037407, and MAE: 0.037283. The ML model had MSE: 0.040378, RMSE: 0.200943, and MAE: 0.183000. The hybrid model's MSE: 0.013982, RMSE: 0.118247 and MAE: 0.110141.

iv. Performance Indicators:

At the same time, based on the comparison of errors when using MTBF and MTTR indicators, it can be concluded that the ML model has the lowest errors (MAE = 0.08508, MSE = 0.19275, RMSE = 0.43903) to offer it as the most suitable for productivity predictions in this case.

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