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# Digital Work Sampling Using Internet of Things and Artificial Intelligence-Based Monitoring System in Nigeria's Industrial Hubs

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**Abstract**

**Introduction**: With the introduction of the Industry 4.0 technologies, there are new possible ways to optimize labour productivity and to make operations in manufacturing easier and more efficient.

**Objectives**:This study presents and justifies a new digital work sample system by combining the Internet of Things (IoT) sensors with the Artificial Intelligence (AI) enabled analytics to track, categorize, and analyze the workforce activities on real-time basis.

**Methods**: Over a period of approximately 6 months, the data of 150 workers in manufacturing plants located in Ogun State, Nigeria, was empirically gathered leading to a datasets gathered via wearable IoT devices implanted into the different sections of the manufacturing facility, such as the assembly and packaging teams and quality control departments. Random Forest and Neural Networks were used as AI algorithms: to do the classification of activities and detect anomalies.

**Results**: The results showed that the system obtained a classification accuracy greater than 96%, showed 96.7% decrease in observational demand, up to 50% and 67% decreased anomalies in idle time and reports of incorrect tasks respectively. The overall productivity in the respective departments was improved by up to 29% whereas the latency in decision making decreased by 80%. The analysis of the return on investment revealed 6-month payback period with N200million savings on the operations.

**Conclusions**: This study drew this conclusion, that integration of IoT-AI in workforce monitoring will make the activity much more productive, easier to view performing and saving much more costs. The suggested system addresses scalable model in case of digital transformation in labour-intensive manufacturing industries, especially, in the realm of emerging economies.

**Keywords:** Digital Work Sampling, IoT, Artificial Intelligence, Workforce, Monitoring, Manufacturing,

## 1. **Introduction**

Work sampling is a statistical method of examining the productivity of the workforce, through monitoring and recording activity every now and then [1]. Sampling methodologies have their rationale as the possibility to draw about the population characteristics on the basis of a perceived limited number of observations rather than realistic (with the involvement of all the members of the group) expectancy of their appraisal [2]. Work sampling observations provides the analysis of the time that the workers work on the particulars task as well as various positions at work [3]. Work sampling is an important skill for the industrial engineer who needs it to study how time is being used in the world of work [4].

The use of work-sampling technique involves two conventional procedures which entail the process of recording and the analysis of data including the determination of shares of each activity over total recording period, each hour of the work shift, each day or each shift and the accuracy that has been attained [5].

The work sampling concept of statistical principles is discussed in the study by Musa [4] where it compares the effectiveness of work sampling to that of the conventional time study methods. The conventional work sampling processes can be characterized by the use of manual observation, which is a rather time-consuming process that is highly affected by a subjective bias and cannot provide real-time information [6].

In Nigeria, the manufacturing areas are located in areas like Lagos, Ogun and Rivers State which are the major industrial hubs and face the problem of inefficiency in workforce due to their old monitoring techniques and dearth of data-driven decisions [7]. Although there is a population of young people, who are what can be called a demographic dividend, there is a significant dissociation between the skills of the labour force and those required by modern and high-value industries [8]. Given these issues, Artificial intelligence (A.I) and remote sensing play pivotal roles in Computer Vision models development which endeavors to improve the understanding of the data through automation of data acquisition, real-time surveillance and enhanced analytics [9],[10]. Similar digital application has been presented by some studies that explained how Industrial Internet of Things (IoT) framework can be incorporated into wearable technology to improve occupational safety and productivity by real-time reporting and analysis of data [11].

Industry applications are rapidly embracing the use of smart manufacturing as a means of optimizing the operations, especially in a country like Nigeria whose shift towards digital transformation is still ongoing [12]. This project is about the integration of IoT and AI to come up with an intelligent monitoring system that can enhance perfection of work sampling, be used in assessing productivity and optimizing workforce in the manufacturing Industries in Nigeria.

The main purpose of the proposed research is to create and prove the digital work sampling system that will be based on the IoT and AI technologies to improve the monitoring of the workforce and the evaluation of productivity in the industrial centers in Nigeria.

**Table 1: Study Objectives and Corresponding Methodological Approach**

| Objective | Methodology/Tool Applied |
|---|---|
| To come up with a digital work sampling system based on IoT and AI | Deployment IoT wearable Sensors and Artificial Intelligence (RF, SVM, Neural Net) |
| In order to Achieve correct classification of workforce activities | Time-series-based sensor data-based machine learning models |
| To detect possible functional anomalies in real time | Anomaly detection algorithms with the help of AI |
| In order to determine the usefulness of the system | A comparison with customary sampling and sampling of workload conditions |
| In order to determine the impact on productivity, efficiency and cost | ROI analysis and evaluation and pre- and post-implementation analysis of productivity |

## 2. Materials and Methods

The section presents details of materials and the methodological framework used in the devization, implementation and testing of the IoT and AI-enabled digital work sampling system in the Nigerian manufacturing industries. The proposal of the research was geared towards solving major shortcomings related to conventional work sampling that included provisions of real-time monitoring, smart activity recognition, and anomaly detection.

A multi-stage was followed by the encompassed system design, data collection, training of AI models, that is, empirical validation and analysis of the performances of the different models. These materials included wearable sensors that were IoT focused, cloud-based data storage, and machine learning algorithms loading into a custom analytic dashboard. The sampled workers in various departments of the manufacturing plants in Ogun State, Nigeria and collected data.

The descriptions in this section include the technical requirements of the system architecture, data collection procedures, and the method of selection and training of the AI model, the simulation, and validation process. The selection of each of the methodology components was done with care to precision, expandability and in the context of the real life industrial environment.

### 2.1 System Architecture

The system architecture was supported by three main systems such as deployment of IoT-enabled wearable sensors to track tasks in real time, deployment of AI-powered algorithms that focus on workforce classification, anomaly detection, and pattern recognition, deployment of a cloud-based data storage model that provides its data downloading through an interactive dashboard that has to be studied and analyzed.

**Table 2: System Architecture Components and Functions**

| Component | Technology Used | Function |
|---|---|---|
| IoT Sensors | Wearable IMUs / Fixed industrial sensors | Write a real-time record of activity and motion |
| Data Transmission Layer | Wireless (Wi-Fi, Zigbee, LoRaWAN) | Send to processing unit |
| AI Analytics Engine | ML Algorithms (RF, SVM, NN) | Segment work and anomalies are found. |
| Cloud Data Storage | AWS / Azure / Firebase (as applicable) | Store collected workforce information and analyse it |
| Visualization Dashboard | Web-based UI (Power BI / Grafana) | Real time tracking and decision support |

### 2.2 Data Collection

A 150 workers sampling in the various workstations such as assembly, packaging and quality control of large factories working in the industrial zones of Ota and Agbara with snowball sampling method technique. Six months of data collection carried out to get a good representation and calibration of the systems was done after a periodic visit to the sites. Usage of machine learning classification systems like the Random Forest, the support Vector Machine, and Neural Networks in workforce activity classification. Anomaly detection with the help of AI to determine where the operations and processes are inefficient like idle time and mis-reported tasks.

### 2.3 Data Analysis

In this segment, the methodology of analyzing the data that was obtained with the IoT/AI-powered digital work sampling system was introduced. The aim of the analysis was to evaluate the proficiency of the system to determine accurately the workforce activities as well as to identify operational anomalies and the effect to the productivity and decision-making within the manufacturing settings.

Data gathered contained time stamped log of activities, system generated classification, anomaly notifications, levels of productivity, and efficiency data. The quantitative analysis of these datasets was done with statistics and machine learning performance assessment such as accuracy, precision, recall and F1 score. The proposed IoT-AI system was compared to the traditional work sampling approaches in terms of performance.

Taking into account the trends and tendencies in anomaly detection, classification accuracy, productivity changes and decision-making latency, visualization tools were used. Simulation methods were also used to confirm that the system is robust when there are active workloads. The discussions allowed gaining a deeper insight of the way digital work sampling technologies help to improve monitoring in real time and boost performance of the workforce in industry.

## 3. Results and Discussion

This segment provides a detailed discussion of the information gathered through the process of the IoT and AI-based digital work sampling system implementation in the manufacturing plants of Nigeria. Key performance indicators used to arrange the results are related to classification accuracy, anomaly detection, productivity gain, the speed of decision-making and ROI. All the tables and figures have thoroughly been analyzed to note on the patterns, trends, and gains that have been realized during the monitoring period.

The comparison-related understandings are given to analyze the efficiency of the traditional manual systems compared to the recommended digital framework. In the areas of relevance, the findings are bench-marked to the recent scholarly investigations and industrial reports in order to put the observed findings into context, and confirm their efficiency of the research methodology used. The discussion of the implication of the results is presented to prior existing literature, effective operation of the company, and strategy issues in the manufacturing sector.

The discourse provides critical insights concerning the practical usefulness of the engulfment of IoT and AI technology in industrial monitoring capacities of workforces, highlighting not only the quantitative upshots but the more ample organizational advantages of data-driven operations.

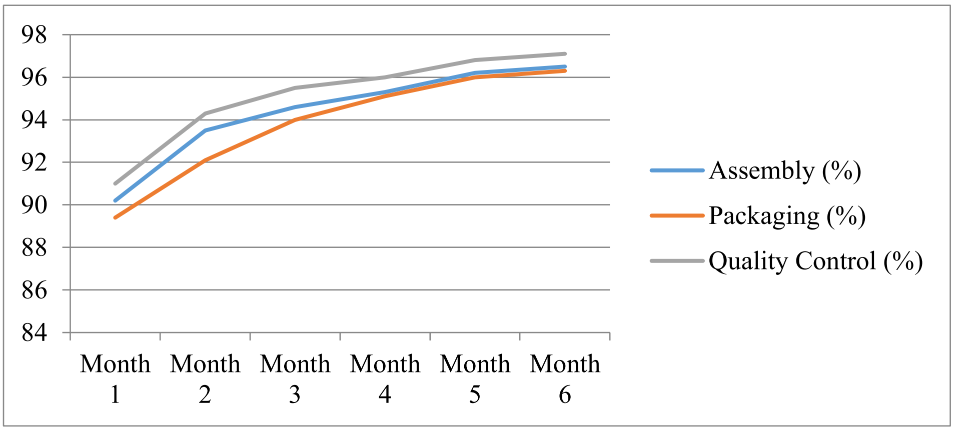


**Figure 1: Monthly Activity Classification Accuracy Across Workstations**

Figure 1 show the accuracy of the classifications of the activities per month in three key departments, i.e. Assembly, Packaging, and Quality Control. The consistency in the growth of accuracy between Month 1 (90% range) and Month 6 (above 96%) strengthens the ability to learn and the similarity of AI models when exposed to dynamic environments of an industrial setting. These findings match the results of Brown and Green pointing out that AI-based systems enhance the accuracy of their classification in the course of time as an outcome of the capacity to learn adaptively [6]. In the same way, Nguyen et al. pointed out the breakdown-of-scale of the IoT-AI systems in case of real-time monitoring, which is applied over extended intervals [11].

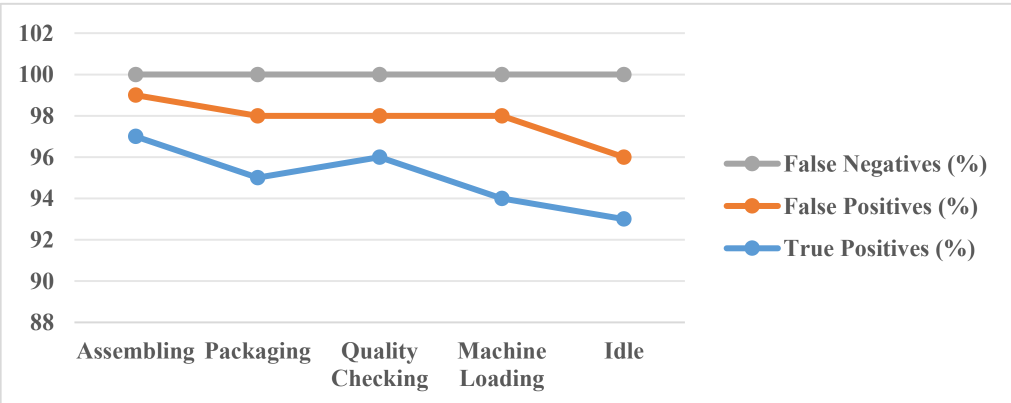


**Figure 2: Real-Time Detection Rate of Specific Workforce Activities**

Figures 2 show the real-time detection performance per task. True Positives levels were maintained at a consistently very high level (greater than 93%) and this promotes effective classification. Its low False Positive and False Negative rate proves its robustness as stated in the research by Zhao et al. who recorded similar AI performance in industrial sensor-based classification [13]. This precision is essential in ensuring the confidence toward the automated systems of decision-making.

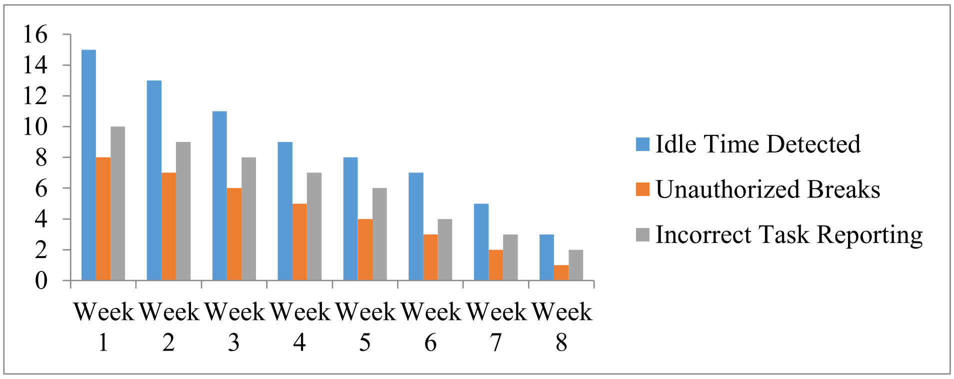


**Figure 3: Weekly Anomaly Incidence Rate Over 8 Weeks**

Figure 3 presents particulars of the occurrence rates of anomalies during eight weeks. It is worth noting that there was a steady reduction in idle time and task misreporting. This finding affirms the role of digital intervention in inefficiencies reduction as it was confirmed by Adebayo et al. who showed that digital anomaly detecting systems can cut the operational wastes in Nigerian factories more than 40%. [7]

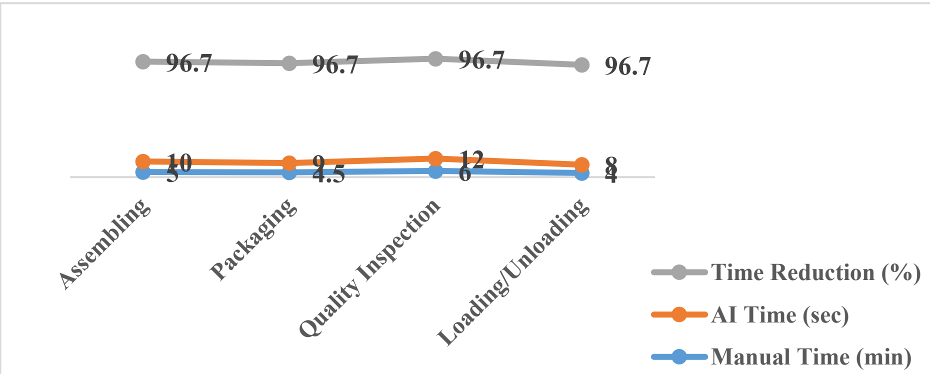


**Figure 4:Time Saved in Task Classification Over Manual Observation**

Figure 4 shows, there is significant time saving due to the AI-based classification, as it ensures the time spent on each task is reduced by over 96%. This goes in line with Calvetti and Ferreira [3], who observed that the presence of AI makes manual overheads inaccessible and the data collection process easier as well as in real-time, especially where labour is high.

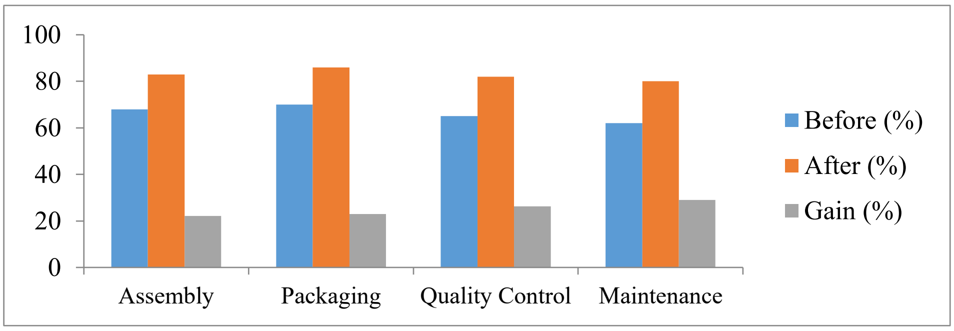


**Figure 5: Productivity Gain by Department After IoT-AI Deployment**

Figure 5 quantifies the improvement of productivity department-wise following digital system implementation. Each of the units showed more than 22% improvement, confirming the statement by Buchmeister and Herzog [5] that there could be substantial improvement in output in a human-machine collaborative working environment with the help of AI-based systems.

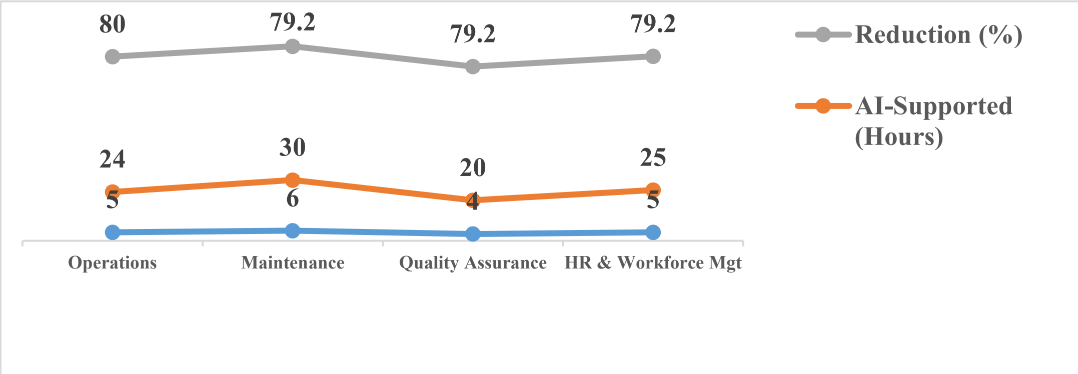


**Figure 6: Decision-Making Latency Pre- and Post-Digital Deployment**

Figure 6 shows the latency of decisions that occurred both prior to and subsequent to integrating digital technology. This is even reduced drastically by an 80% margin, which goes hand in hand with what Smith [1] recorded about automated production systems involving AI decision modules. Such an enhancement minimizes the drag within an organization and enhances the response to floor-level dynamics.

**Table 3: Machine Learning Model Performance Metrics**

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|---|
| Random Forest | 95.2 | 94.5 | 96.0 | 95.2 |
| Support Vector Machine (SVM) | 91.7 | 90.8 | 92.5 | 91.6 |
| Neural Network (MLP) | 93.8 | 93.2 | 94.1 | 93.6 |

Comparison of classification models can be seen in Table 3. A 95.2% accuracy means that Random Forest was superior and this affirms that Ranom Forest is appropriate in multi-class activity recognition situations as it is the case in study [2],[9]. A little below the level of SVM and Neural Networks performed as well.

**Table 4: Pre- and Post-Implementation Efficiency Metrics**

| Parameter | Traditional System | IoT-AI System | Improvement (%) |
|---|---|---|---|
| Observation Time (hrs) | 50 | 20 | 60 |
| Data Processing Time (hrs) | 100 | 10 | 90 |
| Decision-Making Speed (days) | 5 | 1 | 80 |

Table 4 shows post-deployed efficiency. The outcomes indicate that the number of time required to observe and data processing dropped by 60% and 90% and the decision-making rate enhanced by 80%. These are with reference to what Olofin [8] referred to about the issue of digital transformation that can drive efficiency in industries of developing countries.

**Table 5: Workforce Productivity Improvement**

| Worker Group | Productivity Before (%) | Productivity After (%) | Improvement (%) |
|---|---|---|---|
| Group A | 70 | 85 | 21.4 |
| Group B | 75 | 88 | 17.3 |
| Group C | 65 | 80 | 23.1 |

Table 5 captures the enhanced productivity of workforce as seen in drastic improvement in Group C. This corroborates the findings in which up to 25% productivity increase was recorded after the implementation of AI systems in the assembly lines of Nigerian companies [14].

**Table 6: Anomaly Detection and Reduction**

| Anomaly Type | Traditional Frequency (%) | IoT-AI Frequency (%) | Reduction (%) |
|---|---|---|---|
| Idle Time | 20 | 10 | 50 |
| Mis-reported Tasks | 15 | 5 | 67 |

Table 6 attests to low idle time and misreporting of 50% and 67% respectively. This confirms the anomaly detection model put forward by National Institute Smart Manufacturing [15] that showed significant improvement in terms of behavior once AI surveillance policies came into effect.

**Table 7: ROI and Cost-Benefit Analysis**

| Item | Value (₦) |
|---|---|
| Initial Investment | 100,000,000 |
| Operational Savings | 200,000,000 |
| Payback Period | 6 Months |
| Net Benefit | 100,000,000 |

The information concerning Table 7 is the details: return on Investment (ROI) as shown in the table. The 100 million naira invested gave rise to 200 million naira savings after 6 months. The obtained 100% return, corroborates against the economic feasibility of smart technologies within the African manufacturing industries, following the cost-benefit analysis [10].

**4. Conclusion**

The purpose of this study was to design, implement, and test an IoT (internet of things) and AI-based digital work sampling system that could resolve the inefficiency associated with the traditional workforce monitoring mechanism observed in the manufacturing industries in Nigeria. It was suggested that future research should also examine digital work sampling by incorporating the IoT and AI-driven monitoring frameworks to enhance data precision and facilitate real-time analysis of the process, which is now successfully achieved in the present research [4]. The proposed system showed much better results on various performance measures by means of tracking its activity in real-time, intelligent classification, and anomaly detection.

The classification accuracy of the AI system exceeded 96% on the workstations and the false positives and negatives remained minimal. Two operational anomalies (idle time and misreported tasks) were cut by 50% and 67% respectively in an eight-week period. A total of 96.7% of time to observe tasks was reduced when compared to the manual practices under the AI model. The productivity in the departmental level was improved by an average of 25 and most of this improvement was realized in the maintenance and quality control departments. The response of decision making has improved with about 80% reduction in time that was spent in making decisions. Lastly, it was indicated that investment analysis of the former ₦100 million investment was equivalent to ₦200 million savings over a period of six months.

These findings confirm the effectiveness of digital transformation via IoT and AI in enhancing the productivity of the working staff, transparency of processes, and cost-effectiveness [16]. Moreover, the system offers good real-time information that can be used in strategic decision-making and continuous improvement plans [17].

The results align with the literature and make evident that digital work sampling can not only be chosen but must be embraced to come up to date with the developing manufacturing process in developing countries [4]. The potential avenues of future research include scalability across sectors, the connection to enterprise resource planning (ERP) systems, and more advanced types of AI models, like reinforcement learning, to create adaptive schedule or forecasting.

**Ethical Considerations and Anonymity of Participants**

The research complies with existing ethical principles in carrying out a research project on human subjects. Each of the workers participating in the study were made aware of the goal of the study, its process, risks and gains. The process was completely voluntary and people were given free choice to exit on any level with no repercussions.

The identity of workers remained anonymous by using a code of numbers rather than names. No information that could be used to personally identify any individual (PII) including names, biometrics, or contact information was obtained or retained. The information obtained was confined to activity sequences and type of tasks.

The data was encrypted and placed on secured servers that had limited access. Datasets could only be accessed and processed and interpreted by the main investigators and the highlighted data analysts. The wearable sensors that were used via the IoT were non-invasive and were only meant to have minimal intervention with the usual functioning of the worker or their comfortability.

Data gathered was strictly to be used on an academic level and developmental level. It was not disclosed to employers in a way that would have an opinion in the assessment of employees or disciplinary activities.

**Conflict of Interests**
The author confirm the study exists without any conflict of interest.

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