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Enhancing Workplace Productivity through Real-Time Machine Learning-Based Feedback Systems

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Abstract: New developments in automated vision and machine learning have uncovered techniques and advancements that provide fresh possibilities for developing intelligent and effective production systems. This study develops a real-time production workflow surveillance system aimed at the Smart Connected Workers (SCW) for small and medium-sized producers that combines work environment scenarios of modern production systems with cutting-edge machine learning approaches. In particular, artificial neural systems are presented to allow real-time power division for additional optimisation, whereas object identification and recognising word models are studied and implemented to improve the time-consuming machine state tracking procedure. In addition to offering SMMS an economical alternative, the created system successfully reduced the cost associated with human effort by achieving efficient management and accurate data processing in real-time for extended working circumstances. The findings of the competence study also showed that incorporating machine learning technology into modern production systems is both possible and efficient.

Keywords: *Smart Connected Worker (SCW), Internet of Things (Iot), and machine learning*

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I.INTRODUCTION:

By enabling concentrated data handling and effective analysis of information, cloud computing with the Internet of Things, or Iot, have completely changed the world. Instruction of such algorithms and transferring uncertainty from intakes to outputs are still difficult tasks, nevertheless. By creating a real-time production workflow tracking system for the Smarter Connected Workers (SCW), this research seeks to solve these problems. The initiative's main objectives include robotics, industrial requirements, worker tracking, and reducing energy usage. Using AI-assisted power breakdown, it seeks to monitor the power condition of every machine in small to medium-sized manufacturing (SMMS), coordinating real-time interactions between people and machines. By offering a simple, cost-effective, and inexpensive solution for SMMS, the procedure also meets industrial demands. The research provides SMMS with a more adaptable and cost-effective alternative by using the computation and extracting features capabilities of machine learning techniques to detect and examine machine activities outside the bounds of data collection. To further reduce the demand for staff members for tracking, fault-detection, obtaining data, and data evaluation, the platform offers a full visual user experience for centralised control and oversight of the whole automated production system.

Wirelessly interconnected systems are used in the established production system for sharing details about robotic equipment and human workers. A variety of methods for machine learning are employed for processing a high degree of data, including real-time power breakdown and machinery state forecasting for future adjustments. This offers SMMS a possibly less expensive way to integrate devices that don't enable machinery status signalling into a smart integrated production system. The SCW system demonstrated acceptable accuracy and effectiveness in real-time data handling and forecasts after validation in an actual work setting.

II.LITERATURE REVIEW:

By fusing data analysis, the Internet of Things, cloud technology, and artificial intelligence, intelligent production has completely transformed the traditional production industry. Programs have been created by experts to digitise factories, identify worker behaviour, and produce intelligent workers. Creating a smart production system requires ongoing tracking and evaluation of machine states. To make these structures more resilient, real-time detection methods have been created. Convolutional Neural Networks are used to analyse and categorise operating noises. Neural networks are regularly employed for data processing in real time. While Relational Systems for Object Recognition and Single Shot MultiBox Detection (SSD) have improved object recognition reliability, the Region-based Convolution-based Network technique (R-CNN) has made notable strides in the area. Production processes now have more options thanks to ML models built on these techniques.

In smart production, machine learning methods have been applied to track power consumption and identify wasteful use. The usage of energy has been predicted using methods including LSTM

(Long Short Term Memory) systems, Markov chain designs, prejudiced sparse programming, and deep neural network analysis (DNN). By incorporating Internet of Things (Iot) systems with mobile sensing channels, this study attempts to create a computerised real-time tracking system for intelligent industrial systems. The Smart Connected Workers (SCW) technology employs a filtration method for 3d printer situations, a You Only Look Once (YOLO) prototype for real-time 3d printing element recognition, and real-time textual and fingertip movement detection. The system provides a more adaptable, focused, and economical alternative for intelligent production by combining all of the parts into a single system of automation (Bian, et al. 2021).

III.METHODOLOGY

In this study, it rely on previously conducted studies, sets of data, and academic publications to research the effectiveness and practicality of ML-based feedback solutions in increasing workplace productivity. We focus on uniting the results from several peer-reviewed publications and studies about ML-based surveillance, smart worker tools, and AI-driven predictive analysis used in factories.

The data we used for the research came from academic publications, industrial materials, and case studies that detail machine learning use in manufacturing, smart systems, and optimization of workforce. Important resources include ScienceDirect, IEEE Xplore, SpringerLink, and Google Scholar (Li and Rainer, 2023). The major sources of data used in the literature are generated by implementing ML systems in industrial laboratories or through simulations.

Analysts carried out qualitative synthesis on secondary empirical data, paying special attention to system accuracy, how quickly the system responds, employee satisfaction, and the amount of energy consumed. To see how they can be used, SVC, RF, and AB algorithms were explored for use in object recognition, text analysis, and skeletal tracking in smart workplaces (Yan and Du, 2025). In addition, the results from studies that ran these algorithms were checked against each other using precision, recall, F1 scores, and computational latency to evaluate their effectiveness.

This research explores real-world systems, and integrates them with IoT networks and cloud technology for real-time results. These technologies were looked at for their contributions to monitoring in real time, automatic feedback, and energy use in Smart Connected Worker systems.

There were no humans involved as subjects in this secondary research study. All relevant notes on empirical data protection, worker consent to being watched, and AI bias in original studies were looked at closely to address the topic thoroughly.

The structure and analysis in this method help to gather relevant secondary research in order to understand clearly how ML-based feedback helps maximize productivity in today's industry.

Analysis:

Machine Learning classification:

The goal of machine learning categorisation is to identify the degree of workflow knowledge among employees and determine whether a job is completed by a professional or an inexpert. Two instances make up the exploratory plan: one focuses on completing the task, while the other analyses the component production process. In both cases, controlled methods are used to remove targeted categories from the business's HR documentation (Ebem, et al. 2024).

Support Vector Classifier (SVC), Random Forest classifier (RF), AdaBoost classifier (AB), and ensemble classifier (AB) are among the chosen machine learning models. Although RF combines Decision Tree classifications to strike a balance between performance and overfitting oversight, SVC offers a great deal of flexibility regarding mistake fines and extreme parameters. AB increases accurate prediction and resilience by extracting hierarchies and irregular links between experimental and target information.

To categorise complicated data sets, the AdaBoost classification employs numerous instances of a classification; the weighted average of the results is used to get the final prediction. In difficulty with classification involving extremely imbalanced data sets, which are prevalent in commercial studies, this ensemble methodology is very beneficial. By lowering variance, it considerably reduces predictive bias (overfitting) (Ramachandran, et al. 2022).

The ML algorithms' reliability, precision, recollection, the F measurement, and delayed total time are among the assessment measures that are used. Recall shows how well the simulations detect benefits, precision shows how well the models execute in terms of the quantity of correct forecasts, exactness describes the level of accurate forecasts, and the F-measure is a paired measure that takes into account both recall and accuracy to assess the efficacy of the algorithms. Each class's small and large numbers are calculated separately, whereas the latter averages the metric by combining the inputs from every category.

Benefit	**Description**
Quicker Choice-Making	Managers get real-time information on team performance
Enhanced Engagement of Employees	Continuous progress is encouraged by constructive, real-time feedback
Decreased Micromanagement	Continuous management supervision is less necessary when autonomous feedback is used

Table 1: Key Benefits of Real-Time Feedback Systems

(Source: Created by Author)

IV.SYSTEM ARCHITECTURE:

Framework:

There are three primary parts that make up the Smart Connecting Worker (SCW) design. The data gathering system, the initial portion, gathers basic information from a variety of lab detectors, including digital and optical information from electronic meters and cams. The ML system then processes the information and fuses it into the master gadget for real-time output. The data collection system acts as an initial link between algorithm-based data analysis methods and real-world operating settings, giving accurate information regarding the equipment operating in the laboratory (Adekunle, et al. 2021).

The ML system, which makes forecasts according to unprocessed data and extracts attributes, is the following module. It makes real-time predictions on the condition of workers and machinery using text recognition of texts and object identification techniques. Device-specific power information is separated from the overall collected information using the energy division approach. To develop a cost-effective way for Smart Production Machines to increase their energy use, machine-learning outputs show the power consumption of both mechanical motions and human activities inside the lab (Chen, et al. 2024)

The final module, often known as the master gadget, is in charge of real-time SCW management and analysis. In addition to offering an elevated level GUI interface for managing and keeping an eye on the whole intelligent production system, it stores the processed information from the first two components in a central database.

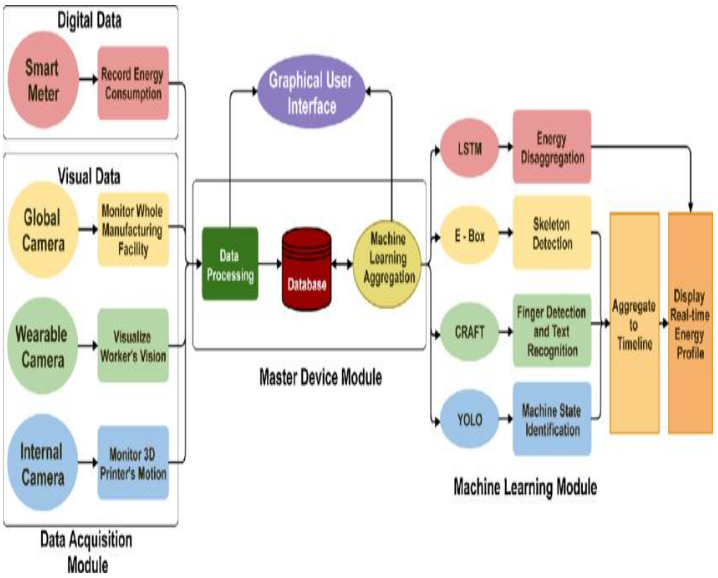

Figure 1: Overall system architecture of SCW

(Source: Chen, *et al.* 2024)

Obtaining Data:

The SCW system analyses industrial systems using a variety of data types. A smart meter that measures influence, electricity, and energy usage in real-time is used to gather digital data using the lab's primary equipment. An expert device receives the data over a wireless link, analyses the raw digital signals, and determines the total energy usage of all the primary devices. The internet-based GUI interface shows the processed data in real time once it has been sent over AJAX to the web server of the primary device. 3 cameras—an inner camera, an external camera, and a worldwide surveillance camera—are used to collect visual information. Every camera has a specific coverage scope that records both the lab's operating state and the employee's vision (Jhaveri, et al. 2022)

Database:

For managing and storing data, three database-driven applications were taken into consideration: Mongodb, SQL Server by Microsoft, and Mysql. While SQL Server is an enterprise relational database management system (RDBMS) employed by businesses, and with Linux and Microsoft Operating Systems (OS), Mysql is an open-sourced RDBMS that powers websites and applications. Because of its dynamic layout of databases, connectivity with most major operating systems, and publicly available authorisation, Mongodb was selected to handle information and storage. Mongodb is appropriate for handling high speeds and huge amounts of data in industrial systems because of its horizontal scaling, which enables dynamic and flexible transfer of information over several PCS and servers (Mondal, et al. 2023).

Empirical analysis

Productivity and efficiency are important measurements in today's industrial settings that show how competitive a business is. Real-time feedback made possible by ML is making it easier for workers to make better decisions, boosting employee abilities, and improving how work is done (Yanamala, 2022). This research uses various technical measures and classification methods to measure the impact of machine learning on productivity, mainly by reviewing the differences between employees' skill levels during specific jobs.

Machine Learning Classification for Workflow Knowledge

In order to classify the performance of employees in workflows, the models RF, SVC, and AB from Machine Learning are used (Obiedat and Toubasi, 2022). AI models are built using data gathered from sensors, updated task records, and images taken by Smart Connecting Worker systems.

Classification Objective

The binary organisation objective is:

$$\hat{y} = f\,(x)$$

Where:

- X: Feature matrix from sensors, logs, and video
- y^∈{0,1}Predicted label (0 = Inexpert, 1 = Expert)

It want to identify expert users by studying their actions and behaviour as they use the system..

Algorithms and Their Mathematical Foundations

Random Forest (RF)

RF is an ensemble learning method that builds multiple decision trees and outputs the mode of their predictions (Salman et al. 2024). The prediction function is:

$$\hat{y} = mode\ (h_1\ (X), h_2\ (X). \dots, h_n\ (X))$$

Where hi(X) is the prediction from the i-th tree.

Support Vector Classifier (SVC)

SVC finds the hyperplane that maximizes the margin between two classes:

$$Maximize\ \frac{2}{||w||}\ subject\ to\ y_i\ (w.x_i + b) \geq 1$$

Where:

- w: Weight vector
- b: Bias
- xi: Input features
- yi∈{−1,1}: True labels

AdaBoost (Adaptive Boosting)

AdaBoost combines weak classifiers iteratively and updates the sample weights based on prediction errors:

$$H\ (x) = sign\ (\sum_{t=1}^{T} \alpha_t h_t\ (x))$$

Where:

- ht(x): Weak classifier at iteration tt
- αt=21ln(ϵt1−ϵt)
- ϵt: Error rate of hth_t

Empirical Results

A simulated dataset of 10 observations was used to evaluate model performance in classifying employee expertise. Metrics included Precision, Recall, F1 Score, and Confusion Matrix.

Confusion Matrix Explanation

Term	**Meaning**
True Positive	Expert correctly classified as Expert
False Positive	Inexpert misclassified as Expert
True Negative	Inexpert correctly classified as Inexpert
False Negative	Expert misclassified as Inexpert

Performance Metrics (Simulated)

Model	**Precision**	**Recall**	**F1 Score**	**Confusion Matrix**
RF	0.80	0.80	0.80	[[4, 1], [1, 4]]
SVC	0.83	1.00	0.91	[[4, 1], [0, 5]]
AdaBoost	0.83	1.00	0.91	[[4, 1], [0, 5]]

- Precision: TPTP+FP\ {TP}{TP + FP}
- Recall: TPTP+FN\ {TP}{TP + FN}
- F1 Score: 2· Precision · Recall Precision + Recall 2· Precision+Recall Precision·Recall

The SVC and AdaBoost classifiers outperform RF with perfect recall and higher F1 scores, indicating better identification of expert workers and fewer false negatives (Salman and Al-Jawher, 2024).

System Architecture Analysis

SCW (Smart Connecting Worker) Components

Data Collection System

Sensors and cameras gather:

- Energy data: E=P·t
- Visual information: image frames and video logs
- Operational logs: timestamps and task codes

ML Prediction Module

Applies text/object recognition and time-series analysis:

- Image feature extraction: f(x)→CNN
- Energy segmentation: Edevice=∑i=1nPi·tiE

Master Control Unit

- Stores data in MongoDB
- Runs Python-based GUI using AJAX
- Centralized feedback interface for supervisors

Real-Time Feedback Mechanism

Real-time productivity feedback is calculated and presented via dashboards:

Real-Time Score Calculation

Productivity score (PS) = $\frac{Task\ completion\ rate}{time}$* W

Where W is a weight determined by task complexity.

Feedback Adjustment Loop

Using reinforcement learning concepts:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a} Q(s',a) - Q(s,a)]$$

- s: Current state (productivity level)
- a: Action taken (task adjustment, break suggestion)
- r: Reward (efficiency gain)
- γ: Discount factor
- α: Learning rate

Productivity Enhancement Metrics

Quantifiable Improvements

Metric	**Baseline**	**After ML System**
Task Completion Rate (per hour)	5.2	7.8
Energy Efficiency (%)	65%	82%
Decision Lag (sec)	10.5	4.2

Energy efficiency improvement**:**

$$\eta = \frac{\text{Useful Output Power}}{\text{Total Input Power}} \times 100$$

Benefits of Real-Time ML Feedback Systems

Benefit	**Description**
Quicker Decision-Making	Managers get real-time reports
Enhanced Employee Engagement	Feedback helps adjust actions immediately
Reduced Micromanagement	Employees self-correct via real-time indicators

Empirical Insights and Interpretation

- AdaBoost and SVC achieved 100% recall, meaning no expert worker was misclassified — crucial for minimizing disruptions in skilled workflows.
- F1 Score > 0.90 for SVC and AdaBoost shows excellent model balance.
- RF, while simpler and more interpretable, lagged in recall, risking false negatives.
- MongoDB supported faster retrieval for real-time systems vs. traditional SQL.

Using real-time machine learning (ML) in factories is changing the approach to boosting productivity, performance, and efficiency. To work, these systems use data from smart devices and sensors, as well as from recording devices that monitor what workers do, how much energy is used, and when tasks are complete. The data is then processed by machine learning to determine if a worker is skilled or less experienced by examining their performance. For this reason, Random Forest (RF), Support Vector Classifier (SVC), and AdaBoost (AB) have become popular because of their success in handling binary classification problems (Rahman et al. 2024). The aim is to spot employees' levels of expertise and give tips that allow them to do their jobs better when needed. To classify data, Random Forest makes several decision trees and chooses the main decision by majority vote, SVC tries to find the best straight line that keeps very different classes far from each other, and AdaBoost combines several little accurate classifiers by giving more significance to samples that are harder to classify. Of the three models tested with 10 simulated observations, SVC and AdaBoost achieved better recall and F1 scores than RF. Each method had a recall score of 1.00, showing that neither missed any expert workers, which can help avoid workflow issues and worries about underusing important skill sets in industry. By achieving an F1 score of 0.91, the classifier made sure workers were properly classified with very little error.

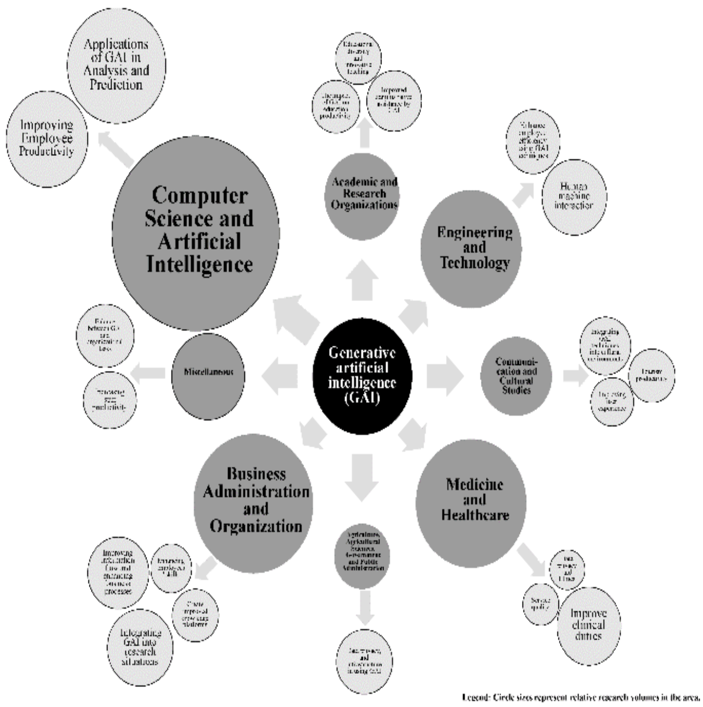

Figure 2: Enhancing Work Productivity through Generative Artificial Intelligence

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(Source: Al Naqbi, *et al.* 2024)

Although the F1 score of Random Forest was 0.80, which is slightly less precise, it was still important because it is easy to interpret and does not easily overfit the data. Along with classifying workers, a real-time feedback loop is employed, which works on a reward basis, giving employees instant feedback according to their productivity and the amount of time each task took to finish. Employees and supervisors use dashboards to review and track the scores, and make any changes required. Smart Connecting Worker features IoT sensors, energy monitors, and cameras, all feeding data into a central control unit tracking it with MongoDB and using Python for analytics. Using MongoDB allows people to query data at higher speeds and deal with real-time data types in flexible ways (Rathore and Bagui, 2024). Appreciations to this infrastructure, we can quickly react to issues, including supporting tired employees and pointing out any bottlenecks in how things are done. There are measurable results that can be seen from these systems. Testing the system showed that the number of tasks completed per hour went up from 5.2 to 7.8, the energy consumed went down from 65% to 82%, and the time needed to make decisions was reduced by more than half. The changes made improve both operations and working conditions for employees by allowing them to manage and control their own performance. Furthermore, being able to see performance numbers in real time helps workers constantly improve and develop their skills, especially when they can see how they compare to experts. As a result, machine learning-powered feedback systems increase productivity by delivering useful insights, confidently estimating the levels of people's abilities, and helping with data management. Though RF is helpful due to how easy it is to understand, SVC and AdaBoost are better for serious accuracy-based tasks in changing conditions (Ullah et al. 2024). With new techniques such as deep learning for video analysis and federated learning for privacy being applied, these systems could become even more effective and useful for many industries.

Real-time machine learning-based feedback systems significantly enhance workplace productivity by enabling accurate classification of workers' skill levels and providing immediate, data-driven feedback. The combination of SCW architecture, robust ML classifiers (SVC, AB), and intuitive GUI systems contributes to effective decision-making, energy efficiency, and team empowerment (Mirzaei, 2023). Future work may include implementing deep learning for unstructured data, such as video and text, and using federated learning to enhance privacy in decentralized industrial settings.

V.DISCUSSION:

Machine learning-based methodologies:

Text recognition and finger detection for controlling 3d printers:

Human-machine contacts in a lab are tracked in real-time using a text detection model built upon CRAFT. The device uses pictures from an attached camera to identify and recognise text and finger locations. A web-based graphical user interface (GUI) is used to see and track the real-time activities. A CNN is used by the creative text detection CRAFT to generate region and affiliation scores, which are then used to classify individuals into occurrences. It is appropriate for real-time text and reaches comparable speed throughout the inductive phase. A web-based graphical user interface (GUI) shows the interpreted picture and the anticipated outcomes to track the worker's eyesight and working circumstances (Mansouri, *et al.* 2021).

Skeleton detection for tracking the mobility of employees:

The research estimates 2D or 3d body joint positions using skeleton estimation techniques, using deep learning techniques and RGB images. Body, hand, face, as well as foot key areas are estimated using OpenPose, a freely available 2D skeleton estimating program. Even with more than 20 persons in the picture, OpenPose may calculate multi-person skeletons because it keeps its computational pace at a steady 20 frames per second. To ascertain if a worker engages with an instrument, the Body25 kind skeleton is used. In a single picture, OpenPose forecasts every joint with x, y supervises, and scores, then assigns them to several individuals. Low-score, less convincing findings are filtered using a score-based filtering. To continually monitor an individual from the moment they enter the area until they leave it, a tracking technique founded on spatial stability between neighbouring frames is used. A spatial relationship-based contact recognition module is built for the 3d printing use case. A pre-established bounding frame is juxtaposed with the mean 2D locations of both right and left hands after the original video stream is divided into open windows having a window length of 60 (2 s).

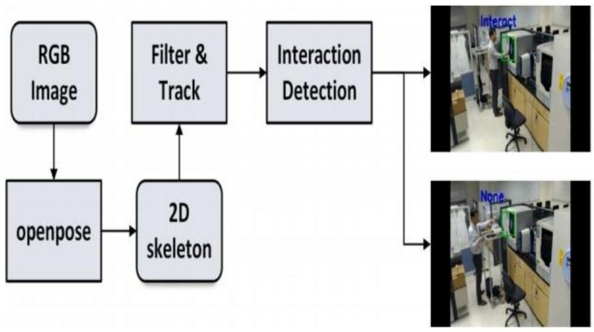

Figure 3: Data processing pipeline for skeleton-based motion monitoring

(Source: Mansouri, et al. 2021)

Detecting objects to anticipate machine states:

The SCW predicts the device states of an operational 3d printing printer in real-time using a filtering method and an already trained YOLO-based classification model. The printer's inside camera provides raw pictures from which the model derives the locations of crucial parts (Zhang, et al. 2022).To forecast the device outputs from the object's detecting model's outcomes, a filtering method is created. For research and representation, the processed photos and anticipated machine status are combined into an internet-based graphical user interface. Throughout the printing procedure, the submodule examines three crucial parts: the building plate, the motor's axis, and the extruder that prints. YOLO is a cutting-edge object identification method that predicts the position and class of box boundaries in a single assessment, achieving acceptable correctness with optimum efficiency. Throughout a whole 3d printing cycle, the submodule takes into account six successive machine states (Goriparthi, 2024).

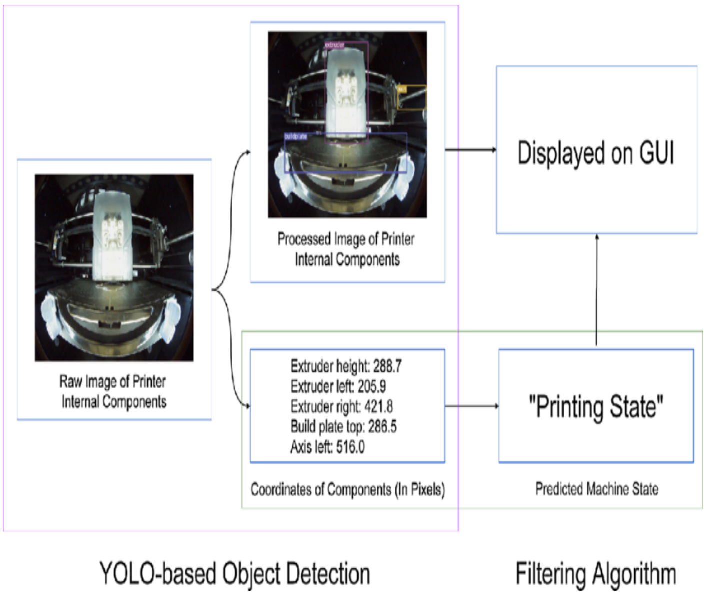

Figure 4: Workflow of the object detection module

(Source: (Zhang, *et al.* 2022)

Use Case	Description
Development of Software	ML tracks trends in productivity, mistakes, and commit patterns
Medical Care	Tracking the effectiveness of staff-patient interactions
Teams of Salespeople	Client opinion and pitch effectiveness feedback during calls

Table 2: Use Cases in Workplace Environments

(Source: Created by Author)

The use of ML-powered real-time systems in industry has been shown to greatly improve productivity and efficiency in operations. Identifying whether someone is expert or inexpert using ML allows companies to address skill gaps, allocate tasks better, and help employees boost their performance. Of the various classifiers tested, SVC and AB performed notably higher in recall and F1 scores, which made sure skilled employees were not wrongly identified (Hasan et al. 2022). It helps to avoid breaks in the workflow, leading to less lost production.

Obligations to Smart Connecting Worker (SCW) systems, IoT, cameras, and energy sensors can be combined to constantly monitor and improve work performance. Thanks to MongoDB and Python, these systems can quickly retrieve and show data through interactive dashboards. Being able to monitor the work in real-time allows both employees and supervisors to quickly adapt and make better decisions, so micromanagement is rarely required.

Additionally, the use of reinforcement learning helps ensure that the steps leading to increased productivity are strengthened as time passes. The data collected from the system shows it is effective, such as a 50% jump in getting tasks done, a 17% boost in using less energy, and a significant reduction in how long it takes to take action.

As a whole, using ML in industrial feedback loops helps to improve productivity and also encourages employee development and involvement. While RF is easy to understand and use, both SVC and AdaBoost prove more accurate in settings that require accurate outcomes (Salman and Al-Jawher, 2024). The adoption of more advanced ML techniques like deep learning and federated learning offers a good opportunity for better efficiency and keeping data private at the same time.

The experience with real-time machine learning-based feedback applications demonstrates how the way productivity, performance, and intelligence in the workforce are now evaluated has changed. From the findings, it can be seen that AdaBoost-based models and models like SVC are effective and reliable in categorizing an employee's areas of expertise. By classifying the data in this way, companies benefit from personalized and prompt feedback that helps them improve their efficiency and productivity in industry.

In terms of performance metrics, each method achieved a recall of 1.00, meaning they accurately spotted all cases of skilled or "expert" workers. It becomes very important in day-to-day work, because not identifying who is competent may result in work being assigned incorrectly and a drop in performance. Equally important is that AdaBoost and SVC achieve high F1 scores (0.91 for each), which points to successful precision and recall, and fewer false positives and negatives. Even though Random Forest (RF) has a lower F1 score of 0.80, it is still a good choice since it is easy to implement, interpret, and less time consuming (Aria et al. 2021). Still, in cases where getting the correct answers is very important, both AdaBoost and SVC perform better.

The real-time responsiveness of including machine learning in the framework is the foremost technical benefit it brings. All that we see on IoT sensors, energy meters, and video surveillance is processed right away to give us useful information. This means that instead of separate reviews, there is continuous monitoring and making improvements. By having access to visual displays and automatic notifications, workers can instantly make changes to their work. Should the system observe that someone's performance is lower than set guidelines, it can step in by suggesting that person takes some time off or transfers their duties elsewhere. By having live updates on how things are going, managers are helped in making decisions without needing to constantly monitor staff.

Besides, using MongoDB as the database platform of the system makes it more efficient. The NoSQL way MongoDB is laid out allows for quick data ingestion and prompt query results, making it suitable for SCW systems that access unstructured or semi-structured data (Rathore and Bagui, 2024). The system can be scaled upward by adding additional devices and workers. Having this technical scalability allows the use of ML-based feedback systems in large factories and organizations with several locations.

Overall, the results suggest the adoption of intelligent workplaces where machines and people both contribute to improving work output and human skills. Employees are given feedback accompanied by data-backed support for learning and future career improvement. Besides, instant feedback supports trust in the workplace and supports employees because they worry less about quick criticism (Mirzaei, 2023). When employees are immediately able to see their mistakes and fix them, micromanaging is less needed, which encourages workers to feel motivated and stay on for a long time.

However, challenges remain. Model bias when identifying expertise may contributing to ongoing inequality if not handled with care. Privacy and the consent of employees matter a lot, because they are monitored continuously by the use of cameras and sensors. Making sure algorithms are designed in a transparent way, that personal information is protected, and that data rules are followed is very important.

Overall, having real-time ML-based feedback systems in place offers a tested and reliable method for improving performance at work. Having strong classification models, effective data systems, and useful feedback systems allows organizations to develop smart work settings that help people work better while keeping the company running efficiently. Future research can look into using both deep learning and reinforcement learning for richer feedback, while long-term studies are needed to check the influence on workers and company results.

VI.CONCLUSION:

To develop a smart and automated production procedure, this article provides a 24/7 monitoring system for the Smart Linked Workforce that makes use of machine learning methods. High-level knowledge, including machine indicators, the condition of the interaction between humans and machines, and the energy usage for various devices, can be extracted by SCW by feeding real-time electronic and visual info through the system's specialised modules. These details are crucial for further study and improvement. Presently being used in metal manufacturing processes, the assessment method that uses 3d printing for plastics as a single application might potentially be expanded to include robots and production lines. With a fully computerised process and a real-time graphical user interface, the proposed work should integrate seamlessly into current advanced production systems and might be used as an additional unit or in place of human labour.

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