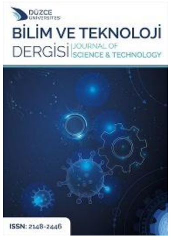

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Research paper

Classification of Construction Roughcasting Activities by Random Forest Algorithm

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ABSTRACT

Effective monitoring and management of construction-site workers is crucial for optimal site management. While traditionally challenging, modern technological advancements have enabled more efficient site control methods. This study employs a machine learning approach using the Random Forest (RF) algorithm to predict roughcasting work activities in a real construction environment. Data was collected using sensors (accelerometer, gyroscope, and magnetometer) attached to a roughcast master's arm. The methodology involved data preprocessing, including missing data control and standardization, followed by task-based labeling. The data was segmented into windows of 100 data points with 50% overlap, and statistical features were extracted. Using an 80-20% train-test split, the RF model achieved an overall prediction accuracy of 88.86% across approximately 234,000 data points representing various activities: waiting (90%), roughcasting (96%), material preparation (86%), and lining (72%). The study, conducted in a real construction environment, focused specifically on roughcasting activities. This approach, utilizing worker-attached sensors and artificial intelligence, demonstrates potential for broader application across construction activities and represents a step toward technological adaptation in construction site management.

Keywords: *Construction Management, Roughcasting Activity, Activity Recognition, Random Forest Algorithm, Construction Labor*

I. INTRODUCTION

Construction is a high-risk industry that impacts economies worldwide. Proper real-time monitoring and management of workers are crucial for productivity and project success (Kim & Cho, 2020). Construction sites are complex, with multiple stakeholders and changing environments. To improve productivity, use of construction technologies is crucial. Industry 4.0 has introduced advanced tech and cyber-physical systems to significantly enhance the construction industry (Boyes et al., 2018). The term Construction 4.0 emerged in 2016 as the construction industry adapts to technological developments (Roland Berger, 2016). Building Information Modeling (BIM), Cloud-based Project Management, Augmented Reality, Virtual Reality, Laser Scanning, Big Data and Analytics, Blockchain, Artificial Intelligence, Internet of Things (IoT), and Sensing Technologies are all being researched for use in the construction industry (Forcael et al., 2020; Antwi-Afari et al., 2020; Karatas & Budak, 2024a). In addition to the construction industry, technologies, especially machine learning, are also used in other sectors (Taşar, 2022).

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To increase worker productivity and construction efficiency, technology can be utilized. However, it is crucial to accurately measure productivity. To achieve this goal, it is important to identify suitable technologies and learn how to use them effectively. Typically, productivity data is gathered manually in traditional construction projects, which can result in inaccuracies. Additionally, manual data collection is a time-consuming and expensive process (Batool et al., 2024; Roberts & Golparvar-Fard, 2019). To enhance worker productivity, it's essential to establish an automated means of collecting data on construction worker activity and recognizing their actions. Recently, researchers investigated construction worker activity monitoring and recognition using various sensing technology tools such as Global Positioning System (GPS), Radio Frequency Identification (RFID), Ultra-Wide Band (UWB), Quick Response (QR) code, smartphones, and Inertial Measurement Unit (IMU) sensors. Using these tools can significantly reduce the time and cost required for data collection (Nematallah & Rajan, 2024; Karatas & Budak, 2024b; Jacobsen et al., 2023; Bangaru et al., 2022; Ryu et al., 2016; Akhavian & Behzadan, 2016; Valero et al., 2017).

Zhang et al. (2018) gathered data from the accelerometers and gyroscopes of nine workers who used smartphones. Their goal was to predict different activities involved in rebar work, such as standing, walking, squatting, cleaning, fetching, placing rebar, locating rebar, banding rebar, and placing concrete pads. They analyzed the data using the Decision Tree (DT) algorithm and found that the model accurately classified the activities with an 89.85% success rate. Ryu et al. (2019) aimed to identify the actions involved in masonry work, such as spreading mortar, laying blocks, adjusting blocks, and removing mortar. To gather data, they utilized an accelerometer sensor worn on the wrist of 10 masonry workers in a controlled laboratory setting. The collected data underwent analysis using K-Nearest Neighbors (KNN), Multi-Layer Perceptron (MLP), DT, and Support Vector Machine (SVM) algorithms, with the SVM algorithm demonstrating the highest accuracy rate of 88.10% in predicting masonry actions. These findings are undeniably valuable in increasing worker productivity. Sanhudo et al. (2021) analyzed data obtained solely from the accelerometer sensor in a laboratory setting. The aim of the study was to classify activities and identify the model with the highest level of accuracy. To achieve this, they utilized several algorithms, including Random Forest (RF), SVM, DT, KNN, and MLP. Joshua and Varghese (2011) investigated accelerometer-based activity classification to automate the recognition of work activities. Using accelerometer data collected from a masonry worker, activities were predicted using DT, Naïve Bayes (NB), and MLP models. The highest prediction accuracy was determined to be 80%, and the results indicated that the proposed method showed potential for automating activity recognition at construction sites. In their study, Karatas and Budak (2021) achieved 90% prediction accuracy using logistic regression, SVM, DT, and KNN algorithms with accelerometer, gyroscope, and magnetometer data obtained from workers. They concluded that this method could automatically detect workers' activities at construction sites with a certain degree of accuracy.

Recently, researchers have been studying ways to monitor construction worker activity. One of the future approaches is to use body-worn IMU sensors and smartphones to track workers' movements and identify their activities. IMU sensors have several advantages, including their adaptability and durability in harsh environments, their compact size, high precision, and reasonable energy consumption. These sensors may be a more suitable option compared to smartphones. This study focuses on the manual labor performed by skilled workers. To achieve more precise outcomes, IMU sensors will be integrated into wristbands for data collection. The end goal is to evaluate the work of construction workers using machine learning algorithms. By exploring the use of IoT in workers, we can enhance their productivity and efficiency on the construction site, ultimately improving project efficiency.

II. MATERIAL AND METHOD

This study aims to predict the activities involved in roughcasting construction activity at the real construction site with high accuracy using a random forest algorithm. Initially, data was collected by attaching IMU sensors to the arm of a worker performing roughcasting on a real construction site. The gathered data was labeled accordingly. The study collected data from the worker's accelerometer, gyroscope, and magnetometer to automatically identify activities in roughcasting work shown in Figure 1. The sensor is attached to the worker's working arm as shown in Figure 1. The sensor is covered with a shirt to prevent damage. The work includes roughcasting (Figure 1a), material preparation (Figure 1b), lining (Figure 1c), and waiting activities. These data were collected at 50 Hz. and over a period of 75 minutes. This study is analyzed using data collected from a single roughcasting worker. Due to the speed and duration of data collection, a substantial amount of data was collected from a single worker. In addition, since activity recognition studies in the literature are analyzed with data collected from a single worker (Antwi-Afari et al., 2020; Ryu et al., 2019; Bangaru et al., 2021; Alemayoh et al., 2021; Al Jassmi et al., 2021; Joshua & Varghese, 2011), the data collected from a single worker in this study is considered to be reliable and sufficient.

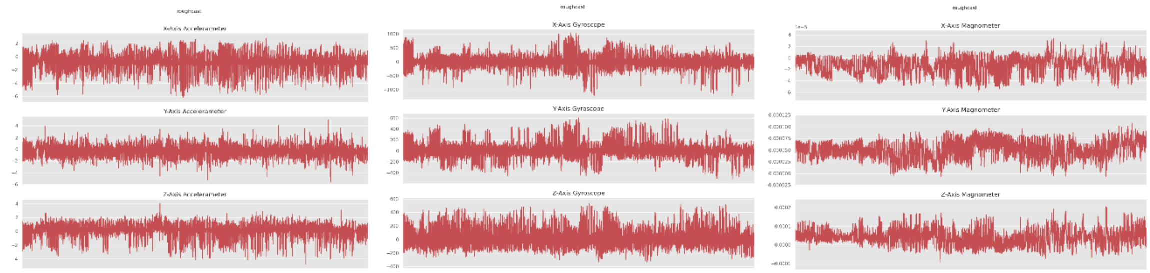
(a)

(b)

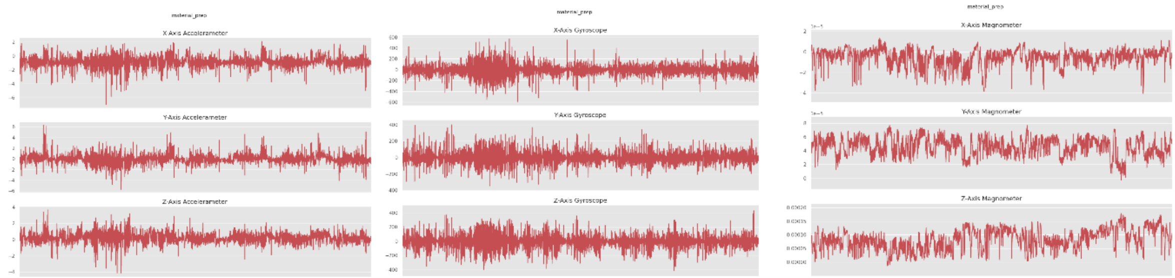
(c)

Figure 1. Construction Roughcasting Activities (a) Roughcasting activity with sensor detail, (b) Lining Activity with wrist band and (c) Material Preparation Activity

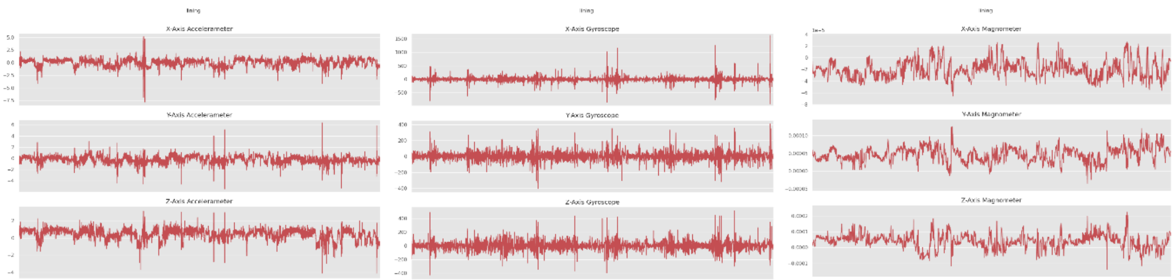
In this study, an accelerometer, gyroscope and magnetometer collected data for four activities: rough casting, material preparation, lining and waiting. Figure 2 shows the accelerometer, gyroscope and magnetometer data in x, y and z axes for all activities.



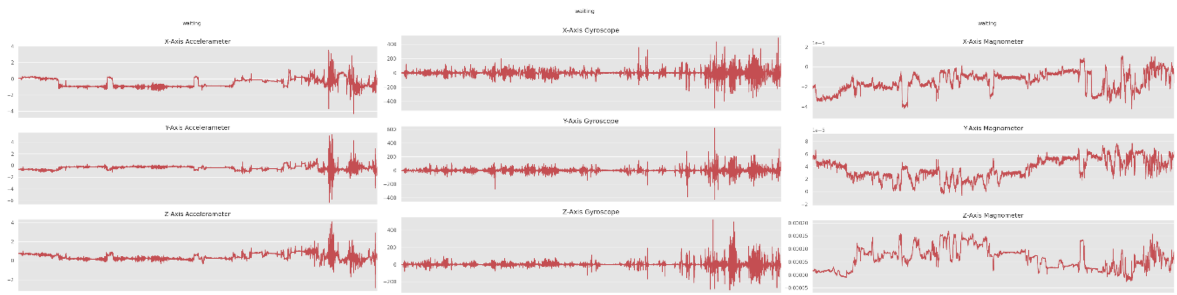
a) roughcast accelerometer b) roughcast gyroscope c) roughcast magnetometer



d) Material Prep. accelerometer e) Material Prep. gyroscope f) Material Prep. Magnetometer



g) Lining accelerometer h) Lining gyroscope i) Lining magnetometer



j) Waiting accelerometer k) Waiting gyroscope l) Waiting magnetometer

Figure 2. The accelerometer, gyroscope and magnetometer data in the x, y, z axis of the all activity

The collected data was labeled and then segmented to prepare it for the model. This involved creating a fixed-width window of 100 data points, starting from the first point, and shifting the window to the next point with 50% overlap until the last point was processed. In these windows, statistical values such as Sum, Median, Mean, Length, Standard deviation, Variance, Root mean score, Maximum, and Minimum were calculated for each accelerometer, gyroscope, and magnetometer data, followed by feature extraction. The data values were standardized to improve model accuracy, with a mean of 0 and a standard deviation of 1. Figure 3 shows both the raw data and the data ready for use in the model.

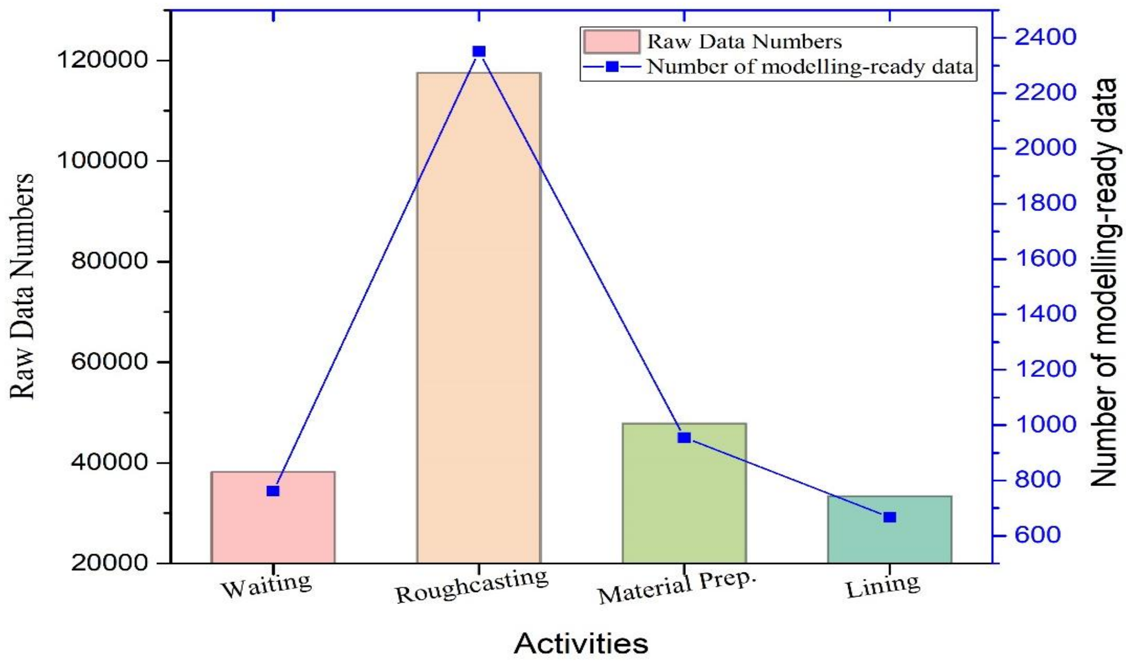


Figure 3. Raw and Modelling-Ready data numbers

In such analyses, when raw data is processed and prepared for modeling, it is divided into training and testing datasets for analysis. The training data is analyzed, and prediction accuracies are calculated by comparing the obtained predictions with the test data. While these division criteria vary in the literature, a common split ratio of 80-20 for training and testing data is generally employed (Joshua & Varghese, 2011; Karatas & Budak, 2021; Altheimer & Schneider, 2024; Meng et al., 2023). Therefore, in this study, the data analysis methodology involved dividing the dataset into two distinct categories: training data (80%) and test data (20%). To determine the accuracy of the predictions, the results from analyzing the training data were compared with the test data. For this study, the researchers used the random forest machine learning model to analyze the training data. In the analysis, 10-fold cross-validation (CV) was performed to ensure the model's randomness and eliminate data bias. The data was divided into 10 layers, with one layer used as validation and the remaining nine for training in each round. CV accuracy values were obtained by averaging the accuracy values for each layer (Figure 4).

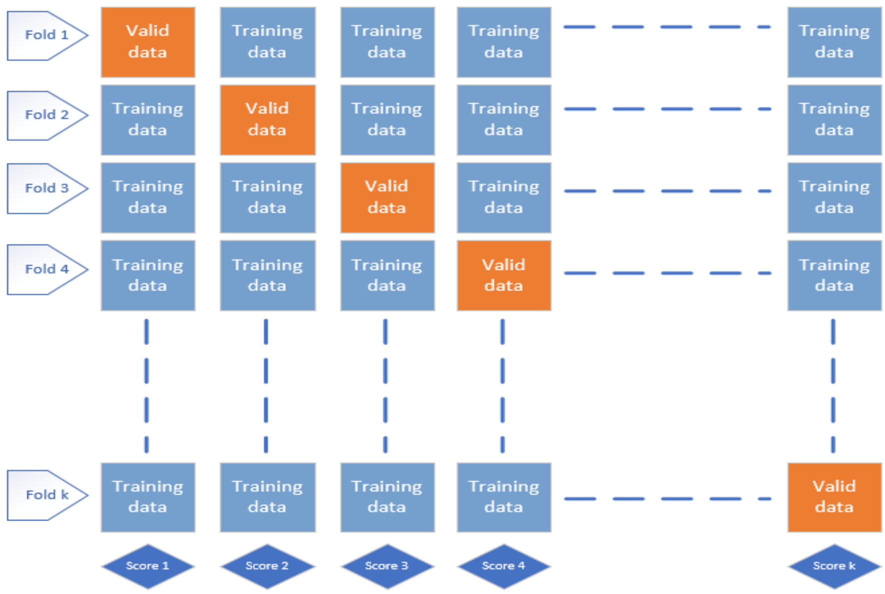


Figure 4. k-fold Cross Validation Process

The DT algorithm is one of the most robust classifiers for activity recognition analysis (Akhavian & Behzadan, 2016). This algorithm partitions the training data in feature space into nodes, assigning each class to a specific region. It examines the discriminative capabilities of extracted features by establishing a set of rules for classification (Hastie et al., 2009; Antwi-Afari et al., 2018). The RF algorithm, which is constructed by combining multiple decision trees, has emerged as a more robust modeling approach. The use of the RF algorithm in decision trees is a powerful non-parametric technique that enhances their resilience and effectiveness by merging them. This methodology involves using bootstrapping and bagging sampling methods to select a sample from a cluster. Additionally, the feature substitution technique is utilized to generate a group of decision trees with controlled variance. In order to combat random forest, noise, and overfitting, the bagging technique is used. This technique involves constructing each decision tree using a modified sample from the training data, with the trees being used as baseline estimators to determine the class label of an unlabeled example through majority vote. The basic decision tree model predicts a class label and casts a vote for it, with the label receiving the most votes being used to classify the instance (Ampomah et al., 2020; Balli et al., 2019).

During the study's final stage, the analysis results were evaluated by creating confusion matrices for all models. The values for True Positives (TP) and True Negatives (TN) obtained from these matrices represent the model's correct prediction values, while the False Negatives (FN) and False Positives (FP) values indicate the model's incorrect predicted values. To evaluate the models, accuracy score values were calculated using Eq.1. Additionally, other model evaluation metrics, including precision, recall, and F1 score, were calculated using Equations 2, 3, and 4, respectively. The Receiver Operating Characteristic (ROC) curve was employed for the final evaluation of the obtained model. The ROC curve provides a graphical representation of the relationship between TP and FP rates. The horizontal axis represents the FP rate, while the vertical axis represents the TP rate (Nath, 2017). The model's prediction success rate increases as the curve progresses concavely toward the ideal model and the area under the curve expands.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1\ Score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

III. RESULTS AND DISCUSSIONS

The objective is to predict the four activities performed by a roughcast worker during construction. Data is collected performing activities like roughcasting, material preparation, lining, and waiting. To analyze this data, the random forest machine learning algorithm is utilized, initially creating confusion matrices. From the analysis results, it is possible to determine the accuracy of predicting each activity. The confusion matrices obtained from Figure 5 show that the roughcasting activity is predicted with 96% accuracy. Additionally, waiting, material preparation, and lining activities are predicted correctly with 90%, 86%, and 72%, respectively. It was determined that lining activity was often confused with roughcasting activity. This is because the lining activity was predicted as roughcast in 24% of the cases. It is also seen that the material preparation activity is slightly confused (11%) with the roughcasting activity.

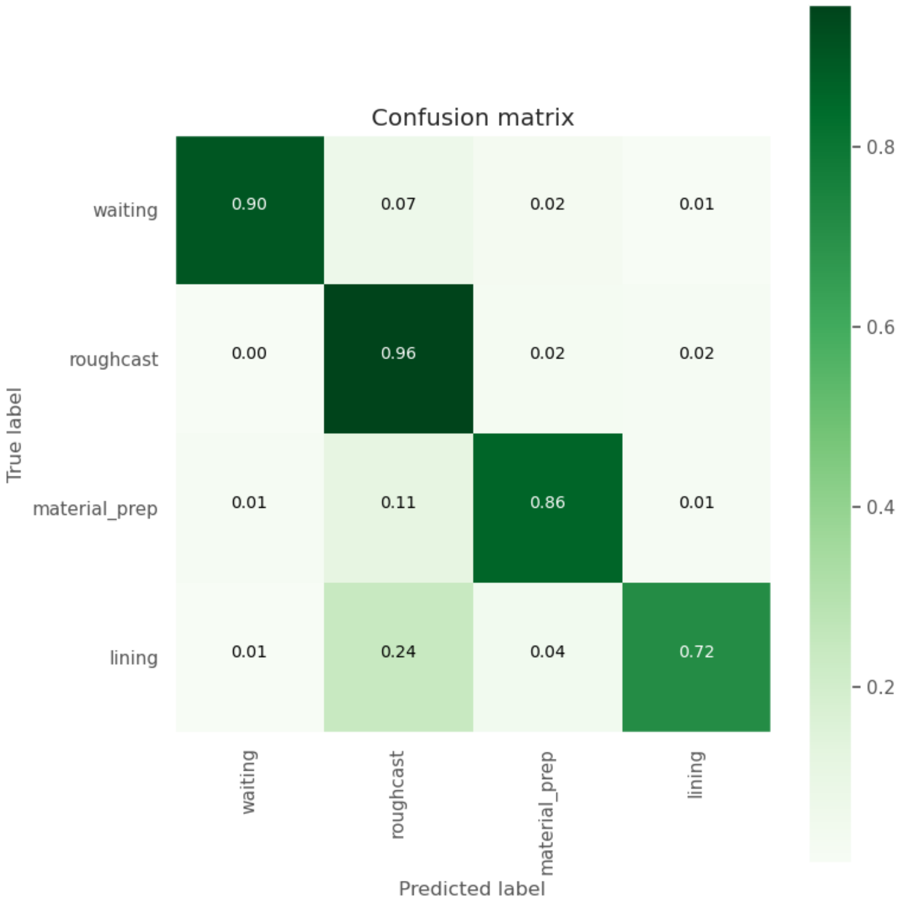


Figure 5. Confusion Matrix of the RF model

According to the results, the Random Forest model demonstrated high accuracy in identifying activities during roughcasting operations. The model's effectiveness was assessed through a comprehensive evaluation approach, utilizing both training accuracy metrics and results derived from 10-fold cross-validation, which provides a more rigorous and statistically reliable method of model validation. During 10-fold cross-validation (CV), the accuracy score may be lower than the training accuracy score. This is due to the fact that the training analysis only performs one analysis, while the CV analysis performs 10 analyses and averages them. Nonetheless, the CV accuracy score is considered a more accurate and robust technique. In the Roughcast activity, the accuracy rate for recognizing four activities was 0.8886. The comparative analysis of different model evaluation metrics used to assess individual activities is presented in Table 1. According to all evaluation criteria, the waiting activity was identified as the most accurately predicted activity, primarily due to its distinctive movement patterns, which significantly differ from those of other activities. Analysis of other activities also revealed generally high prediction accuracy rates. The ROC curve, another evaluation metric, is illustrated in the figure. In ROC curve analysis, the model with the highest prediction success is desired to have the maximum area under the curve. Consequently, the waiting activity was again determined to have the highest prediction accuracy. Based on the average of all activities, the RF model demonstrates successful performance in predicting plastering work activities. The comparative analysis of different model evaluation metrics used to assess individual activities is presented in Table 1. According to all evaluation criteria, the waiting activity was identified as the most accurately predicted activity, primarily due to its distinctive movement patterns that significantly differ from other activities. Analysis of other activities also revealed generally high prediction accuracy rates. The ROC curve, another evaluation metric, is illustrated in the figure. In ROC curve analysis, the model with the highest prediction success is desired to have the maximum area under the curve. Consequently, the waiting activity was again determined to have the highest prediction accuracy. Based on the average of all activities, the RF model demonstrates successful performance in predicting plastering work activities.

Table 1. Model Evaluation metric results of the RF Model analysis of activities

Class Name	Precision	Recall	F1 Score
Waiting	0.9618	0.9042	0.9321
Roughcast	0.8616	0.9586	0.9075
Material Preparation	0.9010	0.8607	0.8804
Lining	0.9035	0.7153	0.7984

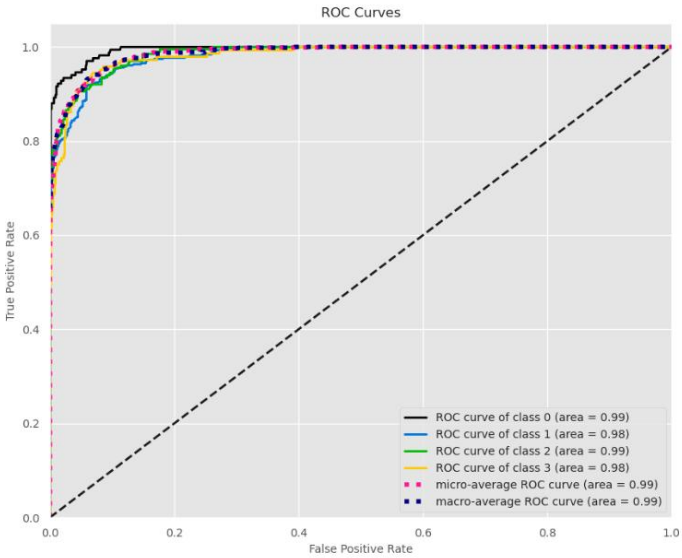


Figure 6. ROC Curve of the RF model

The study shows that sensing technology tools, such as smartphones and Inertial Measurement Unit (IMU) sensors, were utilized to monitor and track construction workers. The collected data revealed that roughcasting, lining, material preparation, and waiting were highly estimated within the study's scope. It is clear that implementing these technologies can significantly enhance worker productivity. Various studies have been conducted to explore different ways of monitoring the activity of construction workers. One such study, conducted by Joshua and Varghese (2011), revealed that the Multi-Layer Perception model, which only relied on accelerometer data, was accurate around 79% of the time. Zhang et al. (2018) analyzed data from accelerometers and gyroscopes using the Decision Tree model, achieving a higher accuracy rate of 89.85%. Ryu et al. (2019) achieved an accuracy rate of 88.10% using only accelerometer data with the Support Vector Machine model in a controlled laboratory environment. Karatas and Budak (2021) conducted a study in a laboratory setting where they used sensors attached to the arms of participants to predict their logging, carrying, surfacing, vibrating, and waiting activities. By employing simple machine learning algorithms, they were able to achieve a prediction accuracy rate of up to 87%. In this study, the RF machine learning model was used and prediction success values close to the studies in the literature were obtained. In this study, the data were collected in a real construction site environment, and not only accelerometers but also gyroscope and magnetometer sensors were used.

IV. CONCLUSION

The rapid development of technology is having a significant impact on the construction industry. Although it is a labor-intensive field, there are ongoing efforts to adapt to technological advancements. Recently, a study was conducted to estimate worker activities through machine learning models, using data collected from construction workers. The study's ultimate goal is to automate the controls carried out by technical staff at construction sites and provide automatic estimation of worker activities, streamlining the construction process.

This study is important for collecting data from construction workers on site. The data was gathered from various sources including accelerometers, gyroscopes, and magnetometers. The collected information was then analyzed using an RF machine learning model to estimate four different activities: roughcasting, material preparation, lining, and waiting. The results of the analysis were quite impressive, with an estimation rate of over 88.86% for the activities. The construction activity with roughcasting activity has the highest prediction success, while the activity with lining activity has the lowest prediction success. This study marks a significant step towards better understanding the intricacies of construction work and improving the safety and efficiency of the industry.

The analyses conducted in this study are believed to be sufficient in identifying worker activities. However, incorporating additional activities into the models or utilizing more advanced models may lead to improved performance estimates. The contribution of this study is expected to enhance productivity measurements, promote continuous monitoring of construction activities, and facilitate automatic activity recognition, ultimately increasing labor productivity at construction sites. Additionally, the development of the artificial intelligence models utilized in this study can lead to the creation of new models. By attaching sensors to workers and automating the tracking of their tasks and activities, more efficient working strategies can be achieved. The utilization of technology in construction management is anticipated to better manage the three construction milestones of time, cost, and quality. Furthermore, the results of this study demonstrate that machine learning models significantly enhance the automatic recognition of worker activities and productivity measurements on construction sites. The developed system provides real-time data to project managers through continuous monitoring and automatic activity recognition features, while automating manual controls previously performed by technical personnel. The sensor-based tracking system not only improves workforce productivity but also enables more effective management of fundamental construction parameters such as time, cost, and quality. The artificial intelligence models developed in this study establish a foundation for future research while contributing to improved workplace safety. In conclusion, the proposed technological approach offers the potential to increase efficiency and reduce costs by modernizing the traditionally labor-intensive structure of the construction industry.

DECLARATIONS

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Ethical Approval and Participant Consent: This study does not involve human or animal participants. All procedures followed scientific and ethical principles, and all referenced studies are appropriately cited.

Plagiarism Statement: This article has been evaluated for plagiarism and no instances of plagiarism were detected.

Availability of Data and Materials: Data sharing is not applicable to this study.

Use of AI Tools: The author/authors declare that no Artificial Intelligence (AI) tools were used in the creation of this article.

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