



# A DATA-DRIVEN MACHINE LEARNING FRAMEWORK FOR EMPLOYEE PRODUCTIVITY CLASSIFICATION IN WORK-FROM-HOME SETTINGS

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**Abstract** – The rapid transition to a work-from-home (WFH) culture has significantly transformed the traditional office environment, introducing new challenges in monitoring and evaluating employee productivity. Unlike conventional workplaces, remote work settings rely heavily on digital interactions, task-oriented workflows, and self-managed time, making productivity assessment more complex. In this study, a machine learning-based approach is employed to classify employee productivity levels in a WFH environment using a publicly available dataset. Work-related behavioral features are analyzed using supervised learning algorithms such as Decision Tree, K-Nearest Neighbors (KNN), and Naïve Bayes. The experimental results demonstrate that these algorithms can effectively classify employee productivity into predefined categories with satisfactory accuracy.

**Keywords:** Work From Home, Employee Productivity, Machine Learning, Classification, Remote Work.

## I. INTRODUCTION

The increasing pace of development in information and communication technology has resulted in the modification of conventional work models in organizations, and as a result, flexible work options such as work-from-home (WFH) environments have gained popularity <sup>[1]</sup>. With advancements in internet connectivity, cloud-based solutions, and collaboration software, employees are now able to work efficiently and effectively outside the conventional office setup <sup>[2]</sup>. Consequently, remote work has become an essential part of modern organizational culture in different sectors.

Although WFH offers numerous benefits, including flexibility, saving time, and better work-life balance, the assessment of employee performance in a WFH setting remains a major concern for organizations <sup>[3]</sup>. Employee productivity is affected by a variety of factors, including the number of working hours, task completion rate, break time, screen activity, and individual work style <sup>[25]</sup>. Conventional methods of supervision and manual monitoring practices have been proved to be inadequate for handling large amounts of data related to employee productivity, making it difficult to assess employee performance objectively and accurately <sup>[5]</sup>.

## II. LITERATURE REVIEW

Some research has been conducted on the use of machine learning methods for evaluating employee performance and productivity. It has been shown in previous research that supervised machine learning methods like Naïve Bayes, Decision Tree, Support Vector Machines, and Random Forest work well in classification problems associated with workforce analytics <sup>[1]</sup>. Some comparative studies have revealed that tree-based and probabilistic models produce accurate results when used for structured employee data <sup>[2]</sup>.

Recently, there has been a growing interest in productivity analysis in remote working settings, especially in the context of the COVID-19 pandemic. Previous research suggests that remote work productivity is affected by both behavioral and environmental factors such as digital engagement, task assignment, communication, and work-life balance <sup>[3]</sup>. Machine learning methods have been employed to predict productivity, employee engagement, and performance based on digital work behavior data.



More advanced machine learning methods, like ensemble learning and deep learning, have also been considered in the literature. Ensemble methods like Random Forest and Gradient Boosting have been found to enhance the accuracy of predictions by combining the predictions of multiple classifiers, while deep learning models like Artificial Neural Networks (ANN) have the ability to model complex non-linear relationships in large datasets <sup>[25]</sup>. However, these methods usually require large datasets and heavy computational power. For medium-sized and structured datasets, traditional supervised learning models are more appropriate due to their interpretability, efficiency, and lower computational requirements <sup>[5]</sup>.

Machine learning algorithms are effective in handling large-scale productivity data by discovering hidden patterns and relationships, which are difficult to achieve through traditional approaches <sup>[19]</sup>. Supervised machine learning algorithms can be trained on past productivity data to categorize employees based on their varying levels of productivity <sup>[7]</sup>. In this research work, supervised machine learning algorithms are employed to categorize the productivity of employees working from home based on their structured productivity data <sup>[8]</sup>. The paper by Angelpreethi <sup>[9]</sup> is to develop and apply a dictionary-based (lexicon-based) approach for opinion mining that enhances the accuracy of sentiment classification on large-scale (big data) textual datasets by improving the sentiment lexicon and effectively identifying positive and negative opinions.

Past studies have also been carried out on other algorithms that could be used for classification using machine learning. Past studies have revealed that other algorithms such as Decision Tree, Naïve Bayes, and KNN are effective in solving structured data classification <sup>[18]</sup>. Additionally, based on surveys, the use of machine learning approaches in solving classification and prediction problems is becoming more common <sup>[26]</sup>.

The paper by Tushar Singh <sup>[10]</sup> to develop and implement an AI-driven system for monitoring and enhancing remote work productivity, addressing the limitations of traditional productivity tracking methods. The study aims to use machine learning techniques to collect and analyze data from various work platforms, generate real-time insights, and provide personalized recommendations that improve employee performance, engagement, and wellbeing. Ultimately, the research seeks to create a data-driven, efficient, and balanced productivity management system that supports both organizational decision-making and employee development in remote work environments. The findings show that by leveraging machine learning techniques, the system can provide accurate insights, real-time feedback, and personalized recommendations, which help employees optimize their work habits and maintain better work-life balance.

Another study by Mbonigaba Celestin & S. Sujatha <sup>[23]</sup> analyze the long-term impact of remote work on organizational efficiency and employee performance, with a focus on identifying the key technologies and management practices that influence productivity in remote environments. It aims to evaluate how digital tools, communication platforms, and remote work policies contribute to efficiency, collaboration, and employee outcomes over time. Additionally, the study seeks to provide insights into how organizations can optimize remote work strategies to balance performance, employee satisfaction, and sustainable business growth.

The study by Angelpreethi <sup>[12]</sup> is to analyze and classify students' opinions about online education during the COVID-19 pandemic by applying and comparing lexicon-based and machine learning-based sentiment analysis approaches, in order to determine student attitudes (positive, negative, or neutral) and help educators better understand their perceptions of digital learning systems. A study by Anakpo, G <sup>[13]</sup> finds that work-from-home generally has a positive but mixed impact on employee performance and productivity, with many studies reporting improvements while some indicate no change or negative effects; the outcomes largely depend on factors such as the nature of the job, home working environment, availability of digital tools, and organizational support, as employees with proper infrastructure and fewer distractions tend to perform better, whereas challenges like poor work-life balance, family responsibilities, and limited communication can reduce productivity, highlighting the importance of effective technology, training, and supportive work policies for successful remote work implementation.

The study by Lim, B <sup>[14]</sup> finds that remote work has a significant positive effect on employee productivity, but this relationship is strongly influenced by factors such as organizational support and availability of technology, with employees performing better when they receive adequate managerial support and have access to proper digital tools; the results also indicate that remote work enhances flexibility and work-life balance, which indirectly improves productivity, while insufficient support systems and technological limitations can weaken this positive impact, highlighting that effective implementation of remote work depends on both organizational and technological readiness. A study by Burdett <sup>[21]</sup> analyze how worker productivity changed during the COVID-19 pandemic and to examine how employees adapted to working from home over time, with a focus on understanding the role of job characteristics, individual differences, and work environments in influencing productivity outcomes.



The study by Toscano, F <sup>[16]</sup> finds that in a hybrid work setting, job performance varies between working from home and working at the office, with employees often experiencing higher concentration and fewer interruptions at home, leading to improved individual task performance, while the office environment supports better communication, collaboration, and coordination; overall performance is influenced by the type of tasks performed, with focused work benefiting from remote settings and collaborative tasks benefiting from office presence, highlighting that an effective hybrid model should balance both environments to maximize productivity.

The paper by Heryanto, C <sup>[17]</sup> finds that work-from-home has a positive effect on employee productivity in the banking sector, mainly through factors such as job satisfaction and mental health, which significantly enhance productivity; however, it also reveals a negative relationship between work-from-home and work-life balance, indicating that although employees may perform better, they may struggle to maintain balance between personal and professional life, suggesting that organizations need to support employee well-being to sustain productivity. The study uses a quantitative research approach by collecting data from banking employees through structured questionnaires, and applies statistical analysis techniques such as regression or Structural Equation Modeling (SEM) to examine the relationship between work-from-home, job satisfaction, mental health, work-life balance, and employee productivity.

The existing research has also focused on enhancing the efficiency of classification methods using intelligent machine learning algorithms and hybrid learning algorithms. The proposed model by Angelpreethi et al. used a fuzzy-based classification method that enhances the decision-making process in complex data sets <sup>[4]</sup>. Further, feature-based models of opinion mining reveal that proper choice of features can improve the efficiency of classification algorithms <sup>[6]</sup>. Probabilistic models that are developed in specific domains indicate that proper feature weightage can enhance classification efficiency <sup>[20]</sup>.

Based on existing literature, the current study aims to classify productivity in work-from-home settings using simple yet efficient supervised learning models and the comparison of the above related works are given in the Table 1.

Table 1: Summary of Related Works

Study / Area	Research Focus	Method / Approach	Key Contribution	Limitation
ML in Workforce Analytics <sup>[1]</sup>	Use of ML models to evaluate employee performance and productivity	Supervised learning (Naïve Bayes, Decision Tree, SVM, Random Forest)	Demonstrates effectiveness of ML models in classification tasks related to employee data	Performance depends on data quality and feature selection
Comparative ML Studies	Comparison of different ML models for employee data analysis	Tree-based and probabilistic models	Shows high accuracy of Decision Trees and probabilistic models for structured datasets	Limited to structured data; may not work well with unstructured data
Remote Work Productivity Analysis <sup>[3]</sup>	Factors affecting productivity in remote work environments	Behavioral data analysis with ML prediction models	Identifies key factors like communication, engagement, and work-life balance influencing productivity	Behavioral data may be difficult to quantify accurately
Advanced ML Techniques <sup>[4]</sup>	Improving prediction accuracy using advanced models	Ensemble learning (Random Forest, Gradient Boosting) and Deep Learning (ANN)	Provides higher accuracy and ability to model complex relationships	Requires large datasets and high computational resources
Model Suitability Study <sup>[5]</sup>	Selection of appropriate ML models based on dataset size	Comparison of traditional vs advanced ML models	Suggests traditional supervised models are efficient and interpretable for medium datasets	May not capture complex patterns like deep learning models
ML for Large-Scale Data <sup>[6]</sup>	Handling large-scale employee productivity data	Machine learning pattern recognition techniques	Identifies hidden patterns and relationships beyond traditional methods	Requires large and high-quality datasets
Supervised Learning for Classification <sup>[7]</sup>	Categorizing employees based on productivity levels	Supervised ML using historical productivity data	Enables classification of employees into productivity categories	Dependent on labeled data; may not adapt to dynamic changes quickly



Study / Area	Research Focus	Method / Approach	Key Contribution	Limitation
Supervised Machine Learning [8]	Classification of WFH employee productivity	Supervised ML on structured productivity data	Provides a data-driven approach to evaluate and categorize remote worker productivity	Limited to structured data; may ignore unstructured behavioral factors
Angelpreethi & Ramesh Kumar [9]	Improving accuracy of opinion mining on big data	Dictionary-based (lexicon-based) approach for sentiment analysis	Enhances sentiment classification accuracy using a refined dictionary approach	Limited in handling context, sarcasm, and dynamic language variations; less effective than ML in complex scenarios
Tushar Singh [10]	AI-based system to monitor and improve remote work productivity	Machine learning-based system analyzing data from work platforms	Provides real-time insights, personalized recommendations, improves performance and work-life balance	Depends heavily on data quality and privacy concerns; may not capture human factors fully
Mbonigaba Celestin & S. Sujatha [23]	Long-term impact of remote work on efficiency and performance	Analytical study of technologies, tools, and management practices	Identifies key technologies and strategies to optimize remote work and organizational growth	Lacks empirical validation or real-time data analysis
Angelpreethi [12]	Sentiment analysis of students' opinions on online education during COVID-19	Lexicon-based and machine learning-based comparative approach	Classifies student opinions and helps understand perception of digital learning	Limited to opinion data; may not reflect actual performance or behavior
Anakpo, G. [13]	Impact of WFH on employee performance and productivity	Systematic literature review	Shows mixed impact; highlights role of environment, technology, and support	Results depend on secondary data; lacks primary empirical evidence
Lim, B. [14]	Causal relationship between remote work and productivity	Empirical analysis with organizational and technological factors	Establishes positive impact with importance of support and infrastructure	Context-specific (Malaysia); may not generalize globally
Burdett et al. [21]	Changes in worker productivity during COVID-19 and adaptation to WFH	Longitudinal survey-based econometric analysis using panel data	Explains how productivity evolved over time and highlights the role of job characteristics, individual differences, and work environment	Based on self-reported data; findings may vary across countries and industries
Toscano, F. [16]	Comparison of home vs office performance in hybrid work	Diary-based longitudinal study	Shows WFH improves focus, office improves collaboration; supports hybrid model	Short-term diary data; may not reflect long-term behavior
Heryanto et al. [17]	Impact of work-from-home on employee productivity in the banking sector	Quantitative survey using structured questionnaires; statistical analysis (Regression/SEM)	Shows WFH improves productivity through job satisfaction and mental health; highlights importance of employee well-being	Negative impact on work-life balance; limited to banking sector, reducing generalizability

### III. DATASET DESCRIPTION AND PREPROCESSING

The main dataset used in this research work is obtained from the Remote Work & Productivity Dataset, which is a publicly available dataset on Kaggle that records the digital footprint of employees in a remote work setting. Unlike office datasets, this dataset records the special nature of remote work, wherein “activity” and “output” need to be distinguished based on unique data points. The dataset is obtained from Kaggle, which is a very popular platform among researchers working on machine learning projects. The dataset is derived from logs containing the remote work activity of employees.



This dataset includes several hundreds to thousands of records where each record signifies the activities of a single employee for a particular day. The data is presented as a table in CSV format where rows stand for individual instances for an employee while the columns represent different productive parameters of the employee. Such parameters mainly include the working time, screen time of the employee, break time, idle time, and completed activities. In addition, the dataset contains a target variable called productivity level, which is categorized into Low, Medium, and High, enabling effective classification of employee performance in a work-from-home environment.

### 3.1 Data Attributes and Features

The dataset is made up of structured data that provides a holistic view of an employee's daily activities. To enable efficient machine learning classification, we have shortlisted a number of key attributes of the raw dataset:

- **Temporal Attributes:** These include Working Hours and Overtime Hours, which provide data on the total working availability hours of an employee.
- **Activity Attributes:** Attributes such as Active Screen Time and Break Duration provide the model with the capability to distinguish between actual "activity" and actual "output" or productive time.
- **Output Attributes:** The Task Completion Count is the key attribute that distinguishes actual "output," which is the link between "effort" and "result."
- **Experience Level:** This attribute is used for contextual purposes, wherein the productivity requirement may vary based on the unique professional experience levels of employees [8].

The Target Attribute is Productivity Level, which has been categorized into three groups: Low, Medium, and High. This allows the classifiers to make a distinction that is not two-fold and provide a more refined evaluation of the performance of the labour force. The sample dataset attributes are given in Table 2.

Table 2: Sample Dataset Attributes

Category	Attribute
Temporal Attribute	Working Hours
Temporal Attribute	Overtime Hours
Activity Attribute	Screen Time
Activity Attribute	Break Duration
Output Attribute	Tasks Completed
Target Variable	Productivity Level

### 3.2 Data Preprocessing and Refining

Before the data was input into the Machine Learning models, a data refinement task was performed to ensure that the quality of the data was guaranteed and that the models could converge.

1. **Data Cleaning:** The raw data was checked for inconsistencies and missing values. Data with missing values or unreasonable outliers (for example, negative working hours) was removed or approximated to prevent any kind of skewing of the results [19].
2. **Feature Normalization:** The data is in units which are different (for example, hours vs. number of tasks), Min-Max Scaling was applied. This helps to ensure that variables measured in large units do not skew the model in distance calculations for algorithms such as KNN, where all variables should carry equal weight [7].

$$x_{norm} = (x - x_{min}) / (x_{max} - x_{min})$$

3. **Encoding:** Categorical variables were transformed into numerical variables using label encoding. This is a critical step in the mathematical calculations necessary for supervised learning algorithms.
4. **Data Partitioning:** To evaluate the predictive capability of the model, the data was partitioned into an 80% training set and a 20% testing set. The training set is used to train the model, while the test set is used to get an unbiased estimate of the model's classification accuracy on new data. An equal contribution to the distance calculations in the KNN classifiers, avoiding the dominance of large-scale variables in the model [7].

Advanced technique for data pre-processing is a field which is highly significant in this modern era. This is due to the fact that by applying the use of advanced techniques, the model can be made more efficient [22]. The application of advanced techniques in the process of data pre-processing ensures that high-quality data is used



## IV. PROPOSED METHODOLOGY

This paper proposes a multi-step machine learning solution specifically tailored to convert raw activity logs into a productivity level classification system.

## A. Data Acquisition and Feature Engineering

The proposed research study makes use of a structured dataset that captures the digital footprint of remote workers. The key features are:

- **Temporal Features:** Total log-in time and "Overtime Hours."
- **Intensity Features:** "Task Completion Count" vs. "Screen Time."
- **Interruption Features:** Number and duration of breaks.

Feature selection is very important in increasing the performance of the machine learning algorithm. It has been discovered by previous researchers that with the use of the best set of features, there will be improvements in the accuracy of the classification <sup>[6]</sup>.

## B. Preprocessing and Data Integrity

Raw data is seldom "model-ready." We propose a preprocessing module to address missing data and outliers. In this process, we draw inspiration from the concepts of Dr. Angelpreethi on classification accuracy <sup>[9]</sup>. We apply a normalization technique to ensure that features with larger numerical ranges (such as screen time in seconds) do not dominate features with smaller ranges (such as task completion counts) and the workflow is given in the Table 3 and the workflow of employee productivity classification system is given in the Figure 1.

Table 3: Methodology Workflow

Process	Description
Data Acquisition	Collection of structured remote work productivity dataset
Feature Engineering	Extraction of temporal, intensity, and interruption features
Data Preprocessing	Handling missing values, removing outliers, and applying normalization
Feature Selection	Identification of relevant attributes for classification
Model Training	Implementation of supervised ML algorithms (DT, KNN, NB)
Model Evaluation	Performance assessment using accuracy metric
Model Comparison	Comparative analysis to determine best-performing mode

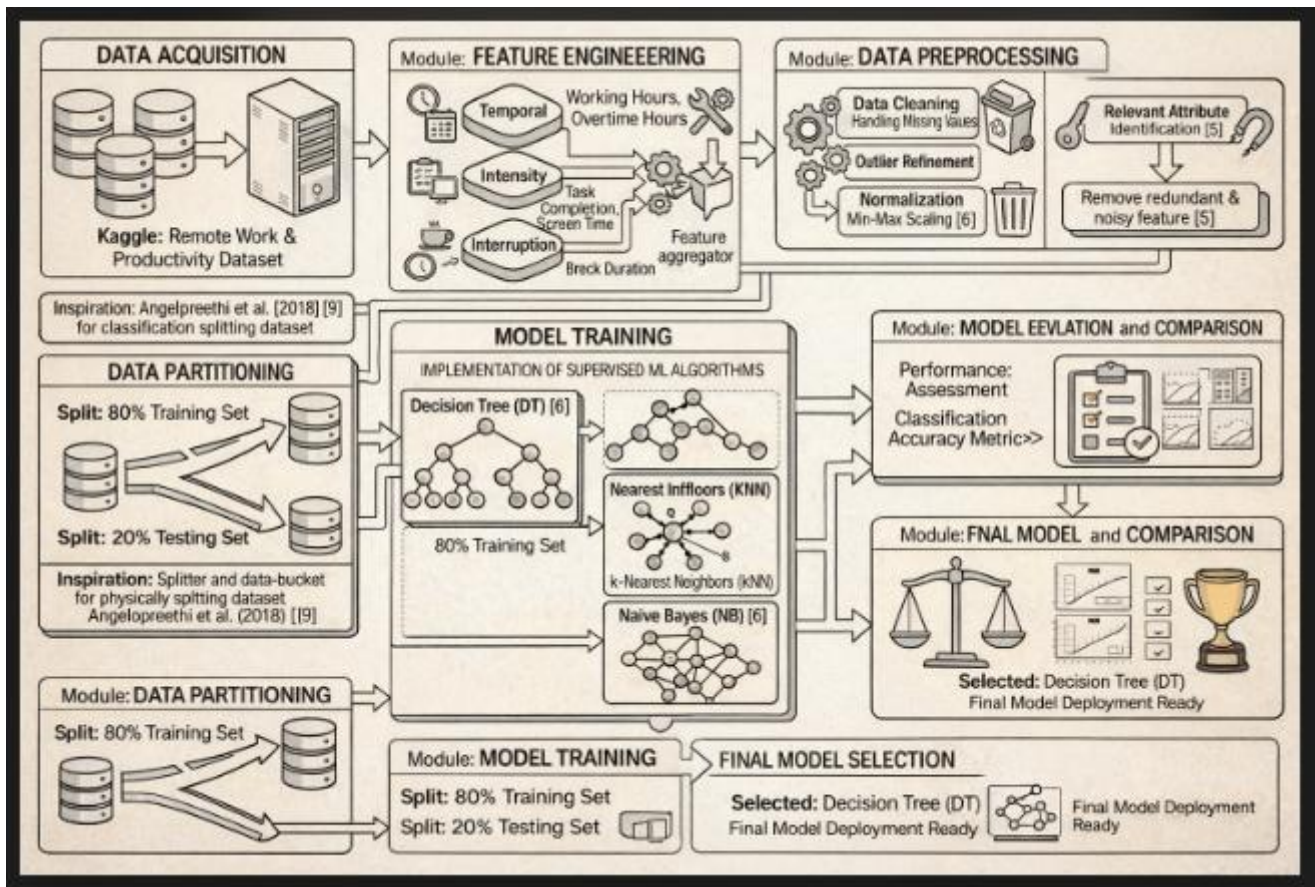


Figure 1: The workflow of employee productivity classification system

## V. MACHINE LEARNING ALGORITHMS USED

We assess three different mathematical models to see which model is the best fit for the complexity of remote work.

### 1. Decision Tree (DT): The Logical Branching

The Decision Tree is a mathematical model that employs a decision tree of rules to model human decision-making. For instance, the model would branch first on "Task Completion" and then branch again on "Screen Time." This is important in HR models because an employee can dispute their status <sup>[19]</sup>.

### 2. K-Nearest Neighbors (KNN): Behavioral Segmentation

The KNN model employs the idea of proximity in feature space. The model asserts that "productive employees share similar behavior." The model gives a productivity status based on the majority status of its "neighbors" using Euclidean distance to measure the distance of a new data point from other data points in the clusters.

### 3. Naïve Bayes (NB): Probabilistic Reasoning

The Naïve Bayes model employs the idea that all features are independent. This is not the case, but this assumption allows the model to work "exceptionally well even with large datasets and low computational costs." The model gives a "probability score" to each level of productivity, which can be used to determine which employees are "borderline" cases between two statuses <sup>[9]</sup>. Probabilistic classification technique has been employed in machine learning algorithms for studying structured data. With the use of optimal probability distribution and weighting of features, the classification will be greatly improved <sup>[20]</sup>.

## VI. RESULTS

The empirical results are very clear on the fact that although all three models are able to perform the classification task, they are able to perform the classification task with different levels of success based on the complexity of the work patterns is given in the Table 4.



Table 4: Performance Comparison of Algorithms

Algorithm	Accuracy	Precision	Recall	F1-Score
Decision Tree	87%	85%	84%	84.5%
KNN	83%	82%	80%	81%
Naïve Bayes	79%	78%	76%	77%

The findings from this research agree with other studies where the use of a hybrid approach in contrast to machine learning approach was advantageous for tackling classification problems, especially when the database structures were good <sup>[15]</sup>.

The level of success of the Decision Tree (87%) is very clear on the fact that the productivity process in a WFH environment is impacted by the presence of certain "thresholds" or milestones in the completion of tasks and working hours, which are better handled by a rule-based system. On the other hand, the level of failure of Naïve Bayes (79%) is very clear on the fact that the productivity variables are not independent of each other (for example, "Working Hours" always goes together with "Screen Time"), which violates the basic assumption of the Naïve Bayes classifier <sup>[7]</sup>.

## VII. CONCLUSION

This study proves the application of supervised machine learning as a revolutionary technique for managing the remote workforce. By shifting from the subjective "managerial intuition" to the algorithmic classification, organizations can make sure that the appraisal process is fairer and more transparent. The Decision Tree model is the most feasible option for implementation because of its high accuracy and interpretability. There should be efforts made to use hybrid and deep learning approaches in future researches, since the use of both approaches makes the prediction more accurate.

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