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Exploring Employee Working Productivity: Initial Insights from Machine Learning Predictive Analytics and Visualization

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HIGHLIGHTS

- Developed a predictive analytical model using machine learning to explore and predict employee working productivity in an organization.
- Employed ranker algorithms to identify and assess the significance of attributes influencing employee working performance in the organizational context.
- Utilized data visualization techniques for descriptive analytics, providing initial insights and correlations among various attributes of employee working patterns.

ABSTRACT

Employee working productivity prediction is vital for effective resource allocation, increased productivity, and upholding a high-performance culture in organizations. However, predicting employee productivity and understanding the root factors influencing working performance pose significant challenges. Traditional human resource management practices often lack data-driven insights, resulting in poor resource allocation and productivity enhancement strategies. To address these challenges, we developed a predictive model using machine learning techniques to determine employee productivity within organizations. Data from an academic institution were collected and pre-processed by encoding relevant features before applying various machine learning predictive models. Experimental results revealed that the linear regression model achieved the best performance in terms of Mean Absolute Error (MAE) and Mean Squared Error (MSE), with values of 0.4878 and 0.4682, respectively. The research findings also highlighted attributes that are imperative in predicting employee performance. Attributes such as "Department," "Actual Productive hours," "Internet Speed," and "COVID-19 adoption month" emerged as highly influential factors across multiple ranking techniques. The data visualization provided valuable insights into various aspects of employee performance, such as productivity trends before and after the pandemic, departmental performance, internet connectivity's impact on productivity, age-related trends, *overtime distribution, and promotion rates. Organizations can use this data to inform workforce planning, address specific challenges in departments, and cultivate an inclusive work environment. By regularly assessing productivity data and implementing recommended strategies, organizations can enhance productivity, create a conducive work environment, and support employee well-being and growth. Future research can explore more advanced machine learning algorithms, incorporate time-series analysis for temporal dependencies, and expand data collection from diverse organizational settings to improve the generalizability of predictive models.*

Keywords: *Employee Productivity; machine learning; prediction; visualization*

INTRODUCTION

Rising costs like meeting minimum wages influence employee management. When workers did not match company culture, they are often encouraged to leave voluntarily. Hence, effective performance evaluation is vital for productivity and resource allocation in workforce management. Thus, an effective evaluation of the employee working performance system is an important factor for workforce management such as sustaining working productivity, optimal resource allocation and employment-related decision making. Inadequate workforce management practices can result in substantial losses for organizations (Sabuj et al., 2023). The current practices of the employee evaluation performance system possess several challenges due to assessment's subjectivity, assessment factors variety, and assessment inconsistencies (Sarker et al., 2018). Furthermore, lack of data-driven approach to predict and improve employee working productivity in organizations. Existing methods may be limited in their ability to capture complex patterns and interactions among various attributes that affect productivity in more specific context or organization (Hu, 2021; Li et al., 2021). Additionally, the absence of effective data visualization techniques hinders the ability to gain valuable insights from data. With the increasing uncertainty and flexibility in the working environment, it becomes even more crucial to analyse employee working performance and identify the factors that affect productivity. Machine learning techniques were applied to build predictive models that can accurately forecast employee working productivity and can identify patterns and correlations that may not be apparent through traditional methods. Data visualization complements machine learning by presenting complex data in a visually intuitive manner. Organizations can gain a deeper understanding of the factors influencing employee productivity. Therefore, the primary objective of this research is to develop a predictive model using machine techniques to determine employee productivity for one of the academic institutions in Sarawak, Malaysia. Various machine learning predictive models were applied to predict employee productivity. Additionally, ranker algorithms were employed to identify the most significant attributes affecting employee working performance. Descriptive analytics techniques by using Tableau software were utilized to visualize, plot, and analyze the data, extracting valuable insights and understanding the correlations among the attributes. By developing predictive model, the institution can optimize their resource allocation, identify areas for improvement, and create a productive work environment. In addition to that, the use of ranker algorithms offers valuable insights into the underlying factors that influence employee productivity within the organization. This paper is organized as follows: first, we present a literature review, followed by the methodology used in the study. Next, we present the experimental results obtained from our analysis, and finally, we draw conclusions and provide recommendations based on our findings.

LITERATURE REVIEW

Machine learning has recently garnered attention for its applications in predicting employee outcomes across diverse organizational settings. In Sarker et al., (2018) study, employee performance evaluation and prediction were conducted using K-Means Clustering and Decision Tree Algorithms. These results serve as valuable inputs for organizational decision-making, aiding in future performance predictions, identifying inefficiencies, and guiding promotions or designations. Tambde & Motwani (2019) addressed the impact of employee churn on company performance by developing an expert prediction system using machine learning. This system forecasts attrition rates, effectively cutting costs and boosting retention. The study explored various algorithms, with Random Forest emerging as the top churn predictor, though it acknowledged machine learning limitations, such as overfitting and underfitting. In Jayadi et al. (2019) research, the Naïve Bayes classification algorithm was employed to predict employee performance and turnover, with the goal of reducing costs and promoting company growth. The prediction model assists HR departments by forecasting and managing employee turnover and performance based on KPIs, job satisfaction, and other relevant factors. Atatsi et al. (2019) conducted a systematic literature review to consolidate knowledge on factors affecting employee performance, emphasizing context and culture, particularly in Africa. Prediction variables included organizational citizenship behavior, leader-member exchange, learning, innovative work behavior, and employee performance. Monisaa Tharani & Vivek Raj (2020) addressed turnover intentions in the IT & ITeS industry using machine learning. Their model identified influential factors, achieving high accuracy with XG Boost and Logistic Regression. Noteworthy variables included job opportunities, gender, education, relocation willingness, job stress, COVID-19 attitude, dependent family, role, satisfaction, commitment, and marital status. Li et al., (2021) developed a prediction model to identify high-performing employees at a publishing house and technology hub, recommending further feature inclusion to enhance the model's performance. Saputra & Purwitasari (2022) studied Fatigue Management in the mining industry, using prediction variables like sleep patterns and drug consumption to create a fatigue prediction model. The Random Forest algorithm outperformed other methods, offering potential for an early warning system to enhance employee performance and reduce accidents. Sabuj et al. (2023) utilized machine learning to predict garment workers' performance, identifying the significant impact of sleep patterns and drug consumption on productivity. Hu (2021) predicted absenteeism in a Brazilian courier company using various machine learning models, achieving the highest accuracy with a combination of Random Forest and AdaBoost. Naz et al. (2022) conducted predictive employee churn analysis in the IoT-enabled software industry, achieving an impressive 98% accuracy with the Chi-squared-based decision tree. Key churn factors included satisfaction level, project count, tenure, and last evaluation. In conclusion, machine learning algorithms show promise in improving employee performance evaluation, prediction, and churn analysis. However, research challenges exist, including model validation, overfitting or underfitting issues, exploring additional prediction factors, considering cultural contexts, and enhancing data collection methods. Future research should address these issues to maximize the potential of machine learning in workforce management and decision-making within organizations.

METHODOLOGY

The methodology section presents an overview of the experimental setup and data analysis techniques employed to investigate the relationship between various factors and employee productivity in our research. This section outlines the key components of our research methodology, including the experimental setup, dataset preparation, feature ranking algorithms, machine learning prediction algorithms, and data description analytics and visualization techniques.

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Experimental Setup and Dataset Preparation

The data acquisition, experiments, data plotting and data visualization were carried out by using the programming environment, libraries and tools using Python libraries based on Spyder 4.2.2 and Tableau Desktop Professional Edition. Specifically, the feature encoding and classifications were performed by using Scikit-learn and Keras libraries. The dataset was collected from one of the higher education institutions in Sarawak. The data has 16 attributes associated with the employee working information and 103 number of instances.

Feature Ranking Algorithms

Feature ranking plays a role in identifying the most relevant and informative attributes within a dataset. The organization can evaluate the relevance and influence of many attributes in predicting employee performance outcomes by prioritizing the features through ranking. In this study, several ranking algorithms were employed including InfoGainAttributeEval (Alhaj et al., 2016), GainRatioAttributeEval , CorrelationAttributeEval (Billson et al., 2021), OneRAttributeEval (Patil, 2014), and ReliefF (Zainudin et al., 2018). These algorithms provide different perspectives and metrics for ranking attribute such as information gain, gain ratio, correlation, simplicity, and discriminative power. By considering multiple ranking algorithms, organizations can gain a comprehensive understanding of the attributes that consistently emerge as influential across different methods.

Machine Learning Prediction Algorithms

The machine learning prediction algorithms provide insights and predictions that can assist organizations in making decisions related to workforce planning, talent management, and performance improvement strategies. In this study, there are various machine learning prediction algorithms have been evaluated for creating a predictive model of the employee working performance. The algorithms chosen for evaluation include Linear Regression (Maulud & Abdulazeez, 2020), Random Forest Regressor (Munir et al., 2023), XGBoost Regressor (Shahani et al., 2021), Decision Tree Regressor (Sishi & Telukdarie, 2021), MLP Regressor (Dutt & Saadeh, 2022), SGD Regressor (Singh, 2022), and Voting Regressor (Erdebilli, 2022).

Data Description Analytics and Visualization

Descriptive analytics plays a crucial role in employee working performance prediction by providing insights into the characteristics, trends, and patterns of the data. In the context of employee working performance prediction, descriptive analytics helps to understand the distribution of attributes related to employee performance, such as working hours, productivity targets, and performance indicators. Correlation analysis helps identify the strength and direction of relationships between variables. To enhance the interpretation and presentation of the findings, Tableau software which is the data visualization tool has been utilized. Tableau enabled to create interactive and visually appealing visualizations effectively communicate the insights derived from the data.

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EXPERIMENTAL RESULTS

This section presents analysis of the findings obtained from our research on employee working productivity prediction. This section encompasses the outcomes of three key components: Feature Ranking, Employee Working Productivity Prediction Model Performance, and Descriptive Analytics and Visualization

Feature Ranking

This section presents the findings and analysis of a study that utilized various feature ranking algorithms, including InfoGainAttributeEval, GainRatioAttributeEval, CorrelationAttributeEval, OneRAttributeEval, and ReliefF. The purpose of feature ranking in employee performance prediction is to identify the variables that have the most significant impact on predicting an employee's performance. By ranking the features, researchers and organizations can determine which variables are most relevant and influential in determining employee performance outcomes.

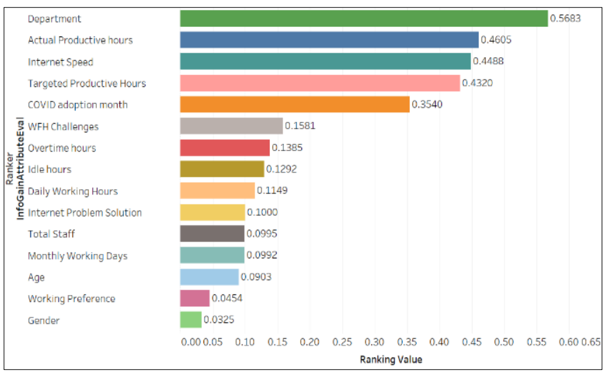


Figure 1. InfoGainAttributeEval

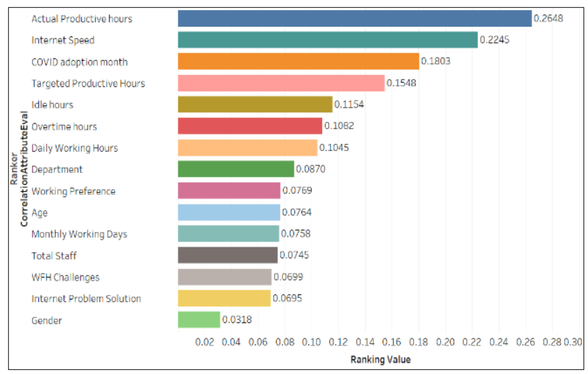
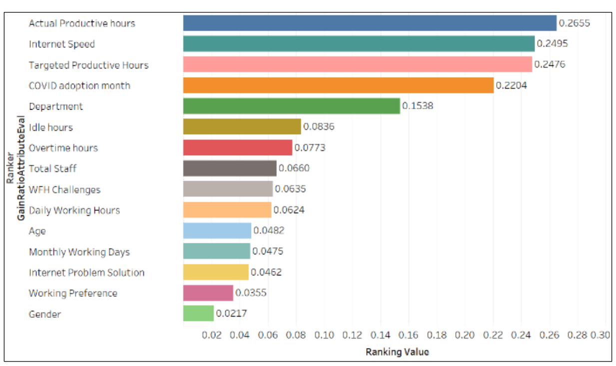


Figure 2. CorrelationAtributeEval



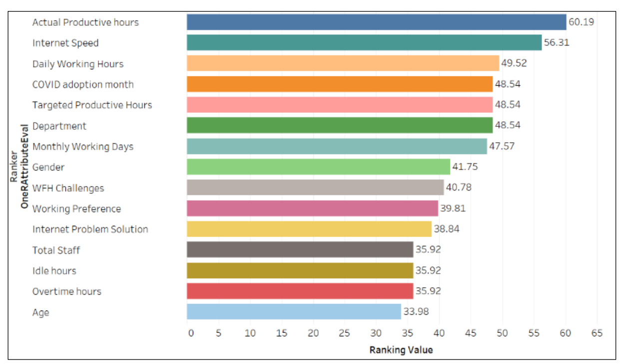


Figure 3. GainRatioAttributeEval

Figure 4. OneRAttributeEval

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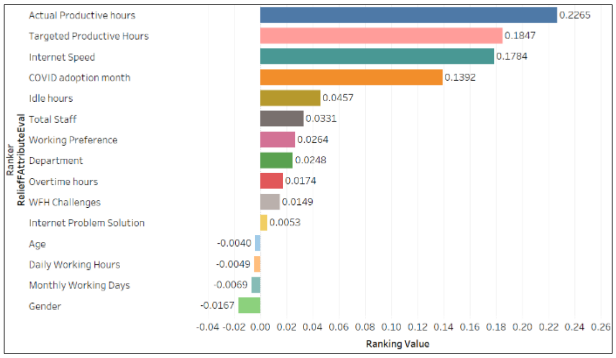


Figure 5. Feature Ranking using ReliefF

Based on the findings from various feature ranking methods, certain attributes stand out as highly influential for predicting employee performance. According to InfoGainAttributeEval, "Department" exhibits the highest information gain score, along with "Actual Productive hours" and "Internet Speed" showing significant contributions. CorrelationAttributeEval highlights strong relationships between performance and attributes like "Actual Productive hours," "Internet Speed," and "COVID adoption month." GainRatioAttributeEval identifies "Actual Productive Hours," "Internet Speed," and "Targeted Productive Hours" as the top attributes, while ReliefFAttributeEval ranks "Actual Productive Hours," "Internet Speed," and "Targeted Productive Hours" as most important. Other attributes also contribute to performance prediction to varying extents. In conclusion, attributes such as "Department," "Actual Productive hours," and "Internet Speed" should receive special attention when formulating strategies to enhance employee performance, considering the context and requirements of the analysis for comprehensive interpretation.

Employee Working Productivity Prediction Model Performance

The experiment aimed to predict employee working performance using various machine learning regression algorithms: Linear Regression (LR), Random Forest Regressor (RF), XGBoost Regressor (XB), Decision Tree Regressor (TREE), MLP Regressor (MLP), SGD Regressor (SGD), and Voting Regressor (KNN). The performance of each model was evaluated using Mean Absolute Error (MAE) and Mean Squared Error (MSE) as shown in Figure 6.

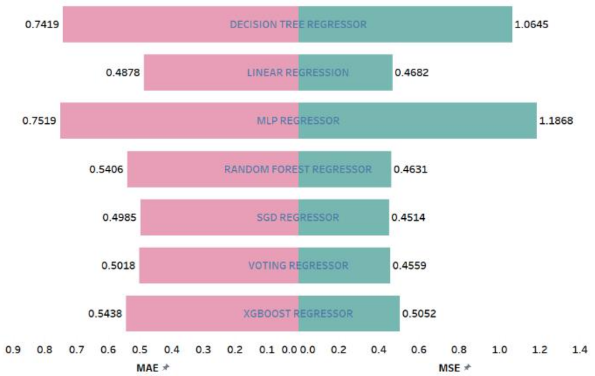


Figure 6. Employee Working Performance Prediction Results

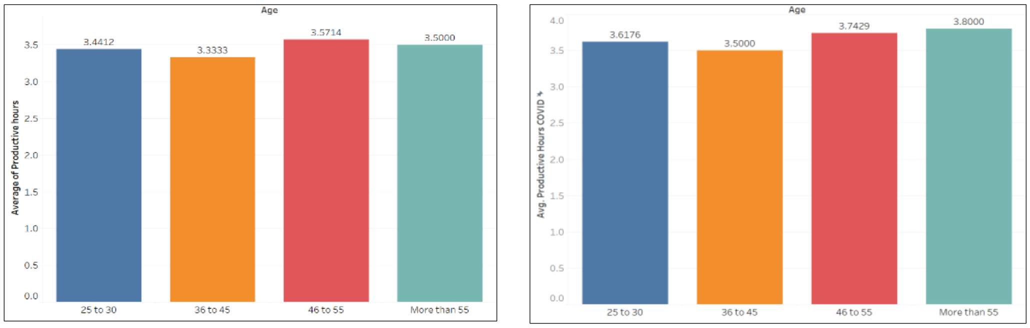
As shown in Figure 6, Linear Regression attempts to fit a linear relationship between the features and the target variable. The achieved MAE of 0.4878 suggests that, on average, the predicted values deviate from the actual values by approximately 0.49 units. The MSE of 0.4682 indicates the mean squared difference between the predicted and actual values, with higher weight given to larger errors. Next, Random Forest Regressor is an ensemble learning method that builds multiple decision trees and averages their predictions. The achieved MAE of 0.5406 indicates that the model's predictions deviate from the actual values by around 0.54 units on average. The MSE of 0.4631 suggests the mean squared difference between predicted and actual values. XGBoost is a gradient boosting algorithm known for its performance in various machine learning tasks. The achieved MAE of 0.5438 shows that the model's predictions have an average deviation of approximately 0.54 units from the actual values. The MSE of 0.5052 indicates the mean squared difference between predicted and actual values. MLP Regressor is a neural network-based model. The achieved MAE of 0.7519 suggests relatively high prediction errors. The MSE of 1.1868 indicates larger mean squared differences between predicted and actual values. Voting Regressor combines the predictions of multiple models. The achieved MAE of 0.5018 indicates a reasonably low average deviation between predicted and actual values. The MSE of 0.4559 suggests a relatively smaller mean squared difference.

The experiment's findings on predicting employee working performance using different regression algorithms revealed that the achieved Mean Absolute Error (MAE) values ranged from approximately 0.488 to 0.752, indicating the average deviation between predicted and actual values. The Mean Squared Error (MSE) values ranged from around 0.451 to 1.187, representing the mean squared difference between predicted and actual values. Despite the variation in MAE and MSE, the overall performance of all regression models was suboptimal, suggesting that the selected algorithms, along with the feature set, may not be the most suitable for accurately predicting employee performance. This highlights the complexity of the task and the need for alternative modeling approaches, feature engineering, data quality improvements, domain knowledge incorporation, and potentially more advanced machine learning techniques to achieve more accurate predictions for employee performance in this specific context.

Descriptive Analytics and Visualization

In this section, we present the visualization component of our research. The analysis in this section focuses on exploring various key aspects related to employee working productivity and its interactions with different factors within the organization. The outlined subsections include Age Versus Productivity, Department versus Actual Productivity Hours, Department versus Working Productivity during the COVID-19 pandemic, Internet Connections Performance versus Working Productivity, Age versus Idle Hours, Age versus Overtime, Age versus Working Promotion, and Age versus Work From Home (WFH) Challenges.

Age Versus Productivity



(a) **(b)**

Figure 7: Employee Productivity by age before Pandemic Covid-19 (a) and after Pandemic Covid-19 (b)

The data illustrated in Figure 7 provides insights into the average productive hours before and after the pandemic for different age groups. Before the pandemic, the average productive hours varied among the age groups. The age group of 25 to 30 exhibited an average of 3.4412 productive hours. The 36 to 45 age group had slightly lower average productive hours at 3.3333. For the 46 to 55 age group, the average productive hours increased to 3.5714. The age group of more than 55 also showed a relatively high average of 3.5 productive hours. After the pandemic, there was a slight overall increase in average productive hours for all age groups. The 25 to 30 age group experienced an average of 3.6176 productive hours, reflecting a moderate increase from the pre-pandemic period. Similarly, the 36 to 45 age group saw an increase to 3.5 average productive hours. The 46 to 55 age group exhibited a further increase to 3.7429 productive hours. The age group of more than 55 had the highest average productive hours after the pandemic, with an average of 3.8.The findings suggest that, in general, there was a slight increase in average productive hours across age groups following the pandemic.

Department versus Actual Productivity Hours

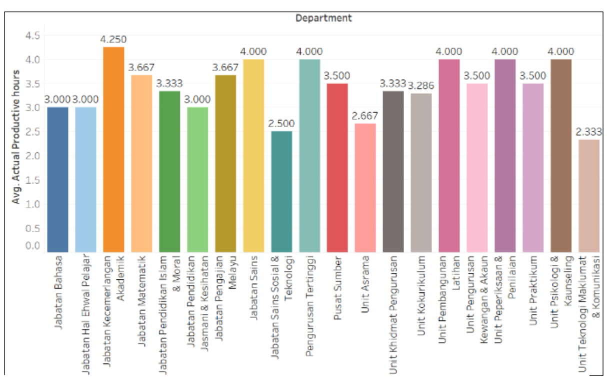


Figure 8: Productivity by Department before Pandemic

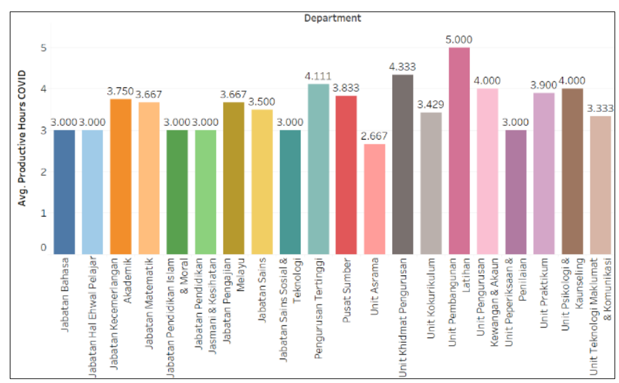


Figure 9: Productivity by Department after Pandemic Covid-19

In Figure 8, Unit Psikologi & Kaunseling and Unit Peperiksaan & Penilaian demonstrated the highest average productive hours, both recording a value of 4. These departments indicate a relatively high level of productivity before COVID-19. Jabatan Pendidikan Islam & Moral, Unit Praktikum, and Pengurusan Tertinggi also display strong average productive hours, with values of 3.78, 3.61, and 4, respectively. These departments showcased above-average productivity levels during the pre-COVID-19 period. On the other hand, Unit Kokurikulum, Jabatan Hal Ehwal Pelajar, Unit Khidmat Pengurusan, and Pusat Sumber exhibit lower average productive hours, with values ranging from 2.89 to 3.21. These departments suggest a relatively lower level of productivity compared to others. The variations in average productive hours across departments highlight potential differences in workloads, effectiveness, or other factors influencing productivity. These findings provide insights into departmental performance and can guide resource allocation and performance improvement initiatives within the organization. Meanwhile, Figure 9 reveals during COVID-19, several departments experienced a decrease in average productive hours compared to the pre-pandemic period. Unit Asrama, Unit Peperiksaan & Penilaian, Jabatan Pendidikan Islam & Moral, Jabatan Sains Sosial & Teknologi, Jabatan Pendidikan Jasmani & Kesihatan, Jabatan Hal Ehwal Pelajar, Jabatan Bahasa, and Unit Teknologi Maklumat & Komunikasi all maintained the same average productive hours as before. However, some departments demonstrated an increase in average productive hours during COVID-19. Notably, Unit Kokurikulum, Jabatan Sains, Jabatan Matematik, Jabatan Pengajian Melayu, Jabatan Kecemerlangan Akademik, Pusat Sumber, Unit Praktikum, Unit Psikologi & Kaunseling, Unit Pengurusan Kewangan & Akaun, Pengurusan Tertinggi, Unit Khidmat Pengurusan, and Unit Pembangunan Latihan experienced a rise in productivity. These findings suggest that certain departments were able to maintain or even improve their productivity levels during the challenging circumstances of the COVID-19 pandemic. The data highlights the resilience and adaptability of these departments in navigating the changes and optimizing their productivity.

Age versus Idle Hours

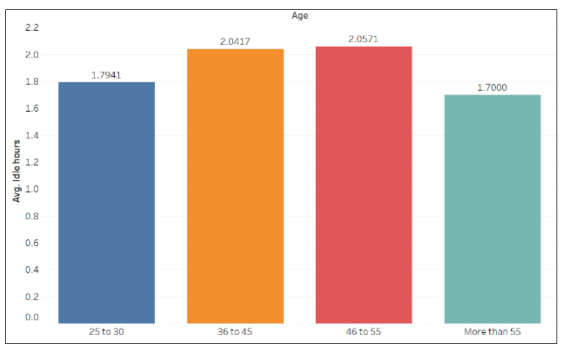


Figure 10: Age versus Idle hours

As visualized in Figure 10, employees in the age group of 25 to 30 exhibited an average of 1.79 idle hours, indicating a relatively lower level of unproductive time. The 36 to 45 age group showed slightly higher idle hours, with an average of 2.04. This finding suggests that individuals within this age range may experience slightly more unproductive time during work. The factors contributing to these idle hours could range from distractions, work interruptions, or potential inefficiencies in task management. Organizations should consider exploring potential strategies to address these factors and optimize productivity. Similarly, the 46 to 55 age group exhibited a comparable average of 2.0571 idle hours. The similarity in idle hours between the 36 to 45 and 46 to 55 age groups may indicate consistent challenges in managing work-related tasks and minimizing unproductive time. Notably, the age group of more than 55 demonstrated a slightly lower average of 1.7 idle hours. This finding is intriguing and suggests that individuals in this age group may have developed effective time management strategies or possess a higher level of task efficiency. However, it is essential to consider that these observations are based solely on idle hours and may not capture the full productivity dynamics within the workplace.

CONCLUSIONS

This research has developed a predictive model using data mining techniques to determine employee productivity within organizations by using various machine learning prediction models and identified the important attributes affecting employee working performance based on several machine learning ranker algorithms. Descriptive analytics techniques aid in visualizing, plotting, and analysing the data, extracting valuable insights and understanding attributes correlations. Among the evaluated models, the linear regression model emerges as the most accurate predictor for employee productivity in the given organizational context, with MAE and MSE values of 0.4878 and 0.4682, respectively. In light of the research findings, it is recommended that organizations consider adopting linear regression for predicting employee productivity. Additionally, implementing effective data visualization methods will help gain deeper insights from the available data. Further research can focus on exploring more advanced machine learning algorithms, incorporating time-series analysis for temporal dependencies, and expanding data collection from diverse organizational settings to improve the generalizability of predictive models.

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CONFLICT OF INTEREST DISCLOSURE

The authors declared that they have no conflicts of interest to disclose.

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