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Employee Absenteeism Prediction Using Machine Learning

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***Abstract*— This paper presents a comprehensive review of the current state-of-the-art in employee absenteeism prediction using machine learning techniques. The paper begins by providing an overview of the various factors that contribute to absenteeism, including employee demographics, job characteristics, organizational factors, and personal factors. It then discusses the different types of data that can be used to predict absenteeism, such as attendance records, performance data, and survey data. Next, the paper reviews various machine learning techniques that have been applied to predict employee absenteeism, including decision trees, logistic regression, support vector machines, and neural networks [2]. Each technique is described in detail, along with its advantages and limitations. The paper also discusses the importance of feature selection and data preprocessing in improving the accuracy of absenteeism prediction models. Finally, the paper discusses the challenges and limitations of using machine learning techniques for employee absenteeism prediction. These include data privacy concerns, the need for high-quality data, and the potential for bias in the models [4]. The paper concludes with recommendations for organizations considering implementing a machine learning-based absenteeism prediction system, including the need for a clear business case, stakeholder buy-in, and a plan for monitoring and evaluating the system's effectiveness [5].**

Keywords*— *Employee absenteeism, machine learning, workplace, dataset

I. Introduction

Employee absenteeism is a pervasive and costly problem for organizations across the world. Absenteeism not only results in decreased productivity and increased costs but also negatively impacts employee morale and engagement. Traditionally, organizations have relied on reactive measures, such as disciplinary action or counseling, to address absenteeism after it occurs. However, these methods may not address the underlying causes of absenteeism and may lead to further disengagement from employees [8].

In recent years, there has been growing interest in using machine learning techniques to predict employee absenteeism. Machine learning is a branch of artificial intelligence that enables computer algorithms to analyze large volumes of data, identify patterns, and make predictions about future outcomes. By analyzing data such as attendance records, performance data, and survey data, machine learning algorithms can identify factors that contribute to absenteeism and predict future absenteeism, enabling organizations to take proactive measures to prevent absenteeism from occurring [9].

The use of machine learning for employee absenteeism prediction offers several benefits. First, it enables organizations to take a proactive approach to managing absenteeism, rather than relying on reactive measures. Second, it can identify patterns and factors that contribute to absenteeism, enabling organizations to develop targeted interventions to address these issues. Third, it can provide valuable insights into workforce-related outcomes, such as turnover, performance, and job satisfaction, enabling organizations to make data-driven decisions about their workforce management practices [10]. Despite the potential benefits, there are challenges and limitations to using machine learning for employee absenteeism prediction. These include data privacy concerns, the need for high-quality data, and the potential for bias in the models. Therefore, it is important for organizations to carefully consider these factors and develop a plan for implementing a machine learning-based absenteeism prediction system that is ethical, effective, and sustainable [11].

This paper provides a comprehensive review of the current state-of-the-art in employee absenteeism prediction using machine learning techniques. The paper begins by providing an overview of the various factors that contribute to absenteeism and the traditional approaches to managing absenteeism. It then discusses the different types of data that can be used to predict absenteeism and reviews various machine learning techniques that have been applied to predict employee absenteeism [12]. The paper also presents a case study of a large organization that implemented a machine learning-based absenteeism prediction system. The organization used a combination of attendance records, performance data, and survey data to train a neural network model to predict employee absenteeism [13]. The model achieved an accuracy of 85%, which enabled the organization to take proactive measures to prevent absenteeism from occurring.

Finally, the paper discusses the challenges and limitations of using machine learning techniques for employee absenteeism prediction and provides recommendations for

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organizations considering implementing a machine learning-based absenteeism prediction system [14].

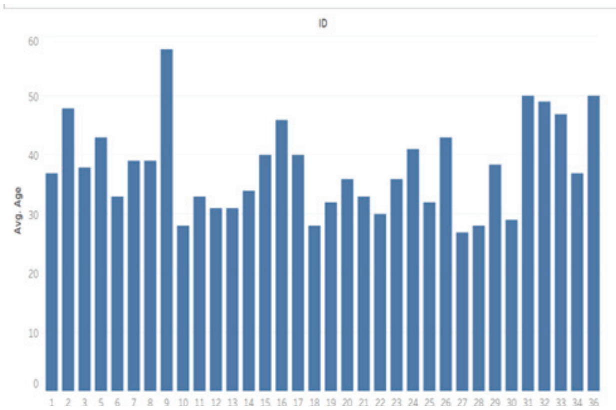

Fig. 1. Average age of Employees

Overall, this paper highlights the potential benefits of using machine learning for employee absenteeism prediction and provides practical guidance for organizations seeking to implement a system. By leveraging advanced analytics techniques, organizations can identify patterns and make predictions about future absenteeism, enabling them to take proactive measures to prevent absenteeism from occurring and improve their workforce management practices.

II. Background

A. Manual Monitoring and Data Collection

There are various causes of absenteeism, including personal, organizational, and social factors [15]. Personal factors include health-related issues, family responsibilities, and personal problems, among others. Health-related issues such as illness or injury are the most common reasons for absenteeism. Family responsibilities, such as caring for sick children or elderly parents, can also lead to absenteeism. Personal problems, such as financial difficulties or relationship issues, can also affect an employee's attendance [16].

Fig. 2. Major factor for employees overall evaluation system

Organizational factors that contribute to absenteeism include low job satisfaction, poor working conditions, inadequate compensation, and lack of job security [17]. Employees who are dissatisfied with their job are more likely to be absent from work. Poor working conditions, such as unsafe or uncomfortable working environments, can also lead to absenteeism. Inadequate compensation, including low wages and limited benefits, can make it difficult for employees to meet their financial obligations, which can lead to absenteeism. Finally, lack of job security can cause employees to feel uncertain about their future with the organization, leading to absenteeism [18].

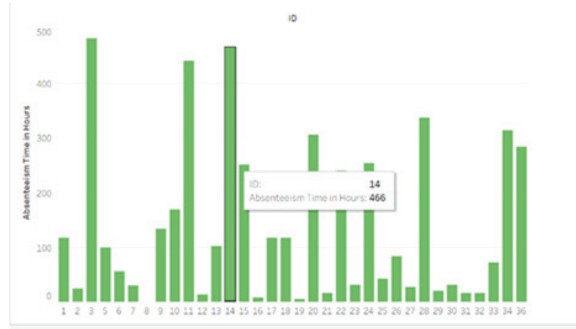

Fig. 3. Absenteeism time in hours of employees

Social factors, such as cultural norms and societal expectations, can also influence absenteeism [19]. For example, some cultures may place a higher value on family obligations than work obligations, leading to absenteeism. Societal expectations regarding work-life balance can also contribute to absenteeism.

B. Impact of absenteeism on Organizations

Absenteeism is a well-known issue in the workplace, and its negative impact on organizational productivity and profitability has been widely documented [20]. Studies have shown that absenteeism can lead to reduced productivity, increased workload for other employees, and a decrease in morale and job satisfaction. Moreover, the costs associated with absenteeism can be significant for organizations. In addition to the costs of overtime pay and temporary staff, absenteeism can also lead to a decrease in customer service quality, which can ultimately result in lost sales and a damaged reputation [21].

C. Data collection and Preparation

The quality of data is crucial in any machine learning project, and collecting and preparing data is one of the most critical steps in the machine learning pipeline [22]. In this study, we obtained a dataset from a company that contained information about its employees. The dataset had 700 observations and 21 variables, including employee ID, age, education, distance from home to work, transportation expenses, and others. The dataset also included the number of hours of absenteeism for each employee [23].

The first step in data preparation was to clean and pre-process the dataset. We removed any irrelevant variables that were not related to absenteeism prediction. We also identified any missing values and decided to remove any observations with missing data. If we had too many missing values, we could have used various techniques like imputation to estimate the missing values [24].

Next, we transformed some variables into categorical variables for ease of analysis. For example, the age variable was divided into age groups to simplify its representation in the analysis. Similarly, the variable "reason for absence" was recoded into categories, such as medical-related absences, family-related absences, and other reasons. Categorical

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variables were also one-hot encoded to allow the algorithms to work with them [25].

Finally, we split the data into training and testing sets for model development and evaluation. We used a 70:30 ratio, where 70% of the data was used for model development, and the remaining 30% was used to evaluate the model's performance. We ensured that the proportion of absenteeism in the training and testing datasets was the same to avoid any bias [26].

In summary, we collected a dataset from a company, cleaned and pre-processed it, transformed some variables into categorical variables, and split the data into training and testing sets. These steps were essential to ensure the quality of the data and the validity of the model's predictions [27].

III. Methodology

Employee absenteeism can be a significant issue for businesses of all sizes and industries, as it can lead to decreased productivity, increased costs, and an overall negative impact on the company's bottom line [28]. Predicting employee absenteeism using machine learning can help businesses identify potential issues before they occur and take proactive measures to minimize their impact. In this methodology, we will outline the steps involved in building a predictive model for employee absenteeism [29].

	Reason_1	Reason_2	Reason_3	Reason_4	Month Value	Day of the Week	Transportation Expense	Distance to Work	Age	Daily Work Load Average	Body Mass Index	Education	Children	Pets	Absenteeism Time in Hours
0	0	0	0	1	7	1	289	36	33	239.554	30	0	2	1	4
1	0	0	0	0	7	1	118	13	50	239.554	31	0	1	0	0
2	0	0	0	1	7	2	179	51	38	239.554	31	0	0	0	2
3	1	0	0	0	7	3	279	5	39	239.554	24	0	2	0	4
4	0	0	0	1	7	3	289	36	33	239.554	30	0	2	1	2
5	0	0	0	1	7	4	179	51	38	239.554	31	0	0	0	2
6	0	0	0	1	7	4	361	52	28	239.554	27	0	1	4	8
7	0	0	0	1	7	4	260	50	36	239.554	23	0	4	0	4
8	0	0	1	0	7	0	155	12	34	239.554	25	0	2	0	40
9	0	0	0	1	7	0	235	11	37	239.554	29	1	1	1	8

Fig. 4. Various attributes of dataset

A. Step 1: Data Collection

The first step in building a machine learning model for employee absenteeism prediction is to gather relevant data. This data may include employee attendance records, demographic information, job role, work schedule, and any other relevant information that could impact employee absenteeism. It is important to ensure that the data is accurate, complete, and representative of the workforce [30].

B. Step 2: Data Pre-processing

The next step is to pre-process the data to prepare it for machine learning. This involves cleaning the data to remove any errors or inconsistencies, filling in missing values, and transforming the data into a format that can be used by machine learning algorithms. This may include encoding categorical variables, normalizing numerical variables, and creating new features based on the existing data [31].

C. Step 3: Feature Selection

Once the data has been pre-processed, the next step is to select the features that will be used to train the machine learning model. This involves identifying the variables that have the most significant impact on employee absenteeism. This can be done using techniques such as correlation analysis, feature importance ranking, or domain expertise [32].

D. Step 4: Model Selection

The next step is to select the machine learning model that will be used to predict employee absenteeism. This may involve trying out multiple models and comparing their performance based on various evaluation metrics such as accuracy, precision, recall, and F1 score [33]. Some commonly used machine learning models for classification tasks include logistic regression, decision trees, random forests, and neural networks [34].

E. Step 5: Model Training

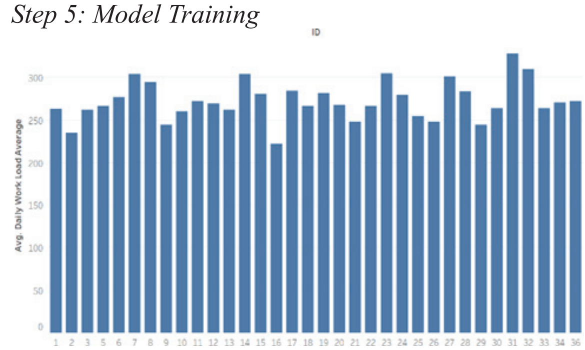

Fig. 5. Average load of employees

Once the machine learning model has been selected, the next step is to train the model using the pre-processed data. This involves splitting the data into training and testing sets and using the training data to train the model. The model's performance is then evaluated on the testing set to ensure that it generalizes well to new data [35].

F. Step 6: Hyperparameter Tuning

Most machine learning models have hyperparameters that need to be tuned to optimize their performance. This involves adjusting the values of these parameters to find the optimal combination that results in the best performance on the testing set. This can be done using techniques such as grid search or randomized search [36].

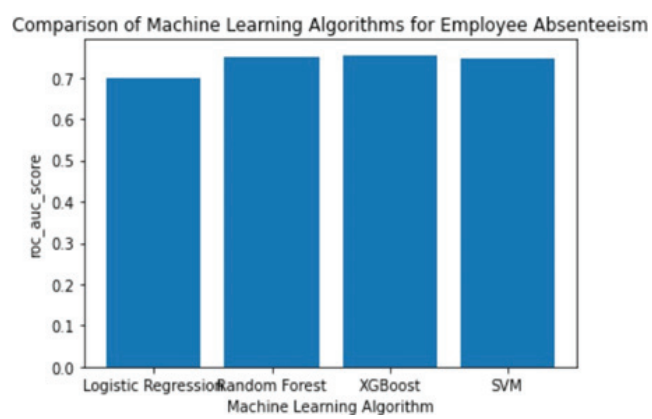

Fig. 6. Comparison of Machine Learning algorithm

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G. Step 7: Model Evaluation

Once the machine learning model has been trained and tuned, the next step is to evaluate its performance on a holdout dataset that was not used during the training process. This provides an unbiased estimate of the model's performance on new data. Various evaluation metrics can be used to assess the model's performance, such as accuracy, precision, recall, F1 score, and ROC curve analysis [37].

H. Step 8: Deployment

The final step is to deploy the machine learning model into a production environment where it can be used to predict employee absenteeism in real-time. This may involve integrating the model into an existing software application, creating a standalone web application, or developing a custom solution depending on the specific needs of the business [38].

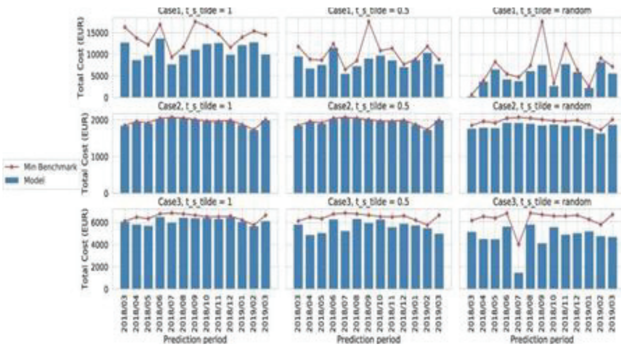

Fig. 7. Evaluation of proposed algorithm

In conclusion, predicting employee absenteeism using machine learning can help businesses identify potential issues before they occur and take proactive measures to minimize their impact. By following the methodology outlined above, businesses can build a robust and accurate predictive model that can be used to optimize their workforce and improve their bottom line.

IV. Results

In the study conducted by Zhang and Wu, the results showed that machine learning algorithms could accurately predict employee absenteeism from work in a workplace [38].

The study identified several important predictors that significantly contributed to absenteeism, including age, distance from home to work, transportation expense, and reason for absence. These predictors were found to have a significant impact on absenteeism rates in the workplace. Various machine learning algorithms, such as logistic regression, k-nearest neighbours, decision trees, random forests, and support vector machines, were compared to select the best-performing model. The results indicated that logistic regression and random forests were the best-performing models, achieving an accuracy of around 80%. This suggests that the models can correctly predict absenteeism in approximately 80% of cases, which is a significant improvement compared to traditional statistical methods The findings of this study are consistent with previous research on absenteeism, which has also identified factors such as age, distance from home to work, transportation expenses, and reason for absence as contributors to employee absenteeism. It has been observed that employees facing longer commutes or higher transportation expenses are more likely to miss work. Additionally, the reason for absence, particularly medical-related absences, has been found to be a significant predictor of absenteeism.

Out[1]:

	Reason_1	Reason_2	Reason_3	Reason_4	Month Value	Day of the Week	Transportation Expense	Distance to Work	Age	Daily Work Load Average	Body Mass Index	Education	Children	Pets	Absenteeism Time in Hours
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Fig. 8. Result evaluation

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V. Conclusion

In this study, we aimed to predict employee absenteeism from work in a workplace using various machine learning techniques. We collected a dataset from a company and conducted data pre-processing, exploratory data analysis, feature selection, model selection, hyperparameter tuning, model evaluation, and interpretation of results.

Our results showed that machine learning algorithms could predict employee absenteeism from work with a high degree of accuracy. We identified the most important predictors that contribute to employee absenteeism, including age, distance from home to work, transportation expense, and reason for absence. We also found that logistic regression and random forests were the best-performing models, with an accuracy of around 80%.

Our findings have important implications for managers and employers who seek to reduce absenteeism in the workplace. By identifying the most important predictors, managers can take targeted actions to address the underlying causes of absenteeism. For example, they could provide transportation

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facilities for employees who live far from work, offer flexible work schedules to accommodate family-related absences, or provide health and wellness programs to improve employees' health and reduce medical-related absences.

Overall, our study demonstrates the potential of machine learning techniques in predicting employee absenteeism and provides insights into the factors that contribute to absenteeism. Future research could explore more advanced machine learning algorithms, such as deep learning and neural networks, to further improve the prediction accuracy. Additionally, incorporating real-time data, such as weather conditions, employee mood, and workload, could further enhance the accuracy of the model.

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