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Article

Predicting the Productivity of Municipality Workers: A Comparison of Six Machine Learning Algorithms

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Abstract: One of the most significant areas of local government in the world is the municipality sector. It provides various services to the residents and businesses in their areas, such as water supply, sewage disposal, healthcare, education, housing, and transport. Municipalities also promote social and economic development and ensure democratic and accountable governance. It also helps in encouraging the involvement of communities in local matters. Workers of Municipalities need to maintain their services regularly to the public. The productivity of the employees is just one of the main important factors that influence the overall organizational performance. This article compares various machine learning algorithms such as XG Boost, Random Forest (RF), Histogram Gradient Boosting Regressor, LGBM Regressor, Ada Boost Regressor, and Gradient Boosting Regressor on the dataset of municipality workers. The study aims to propose a machine learning approach to predict and evaluate the productivity of municipality workers. The evaluation of the overall targeted and actual productivity of each department shows that out of 12 different departments, only 5 departments were able to meet their targeted productivity. A 3D Scatter plot visually displays the incentive given by the department to each worker based on their productivity. The results show that XG Boost performs best in comparison with the other five algorithms, as the value of R Squared is 0.71 and MSE (Mean Squared Error) is 0.01.

Keywords: machine learning; algorithms; productivity; municipality; workers; incentives

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1. Introduction

Organizations strive to enhance employee engagement to improve productivity as they adjust to the new digital era. Productivity helps companies to expand and utilize their human resources. Employees who are engaged are more productive as they are motivated beyond personal factors to perform for the organization (Harter et al. 2013). Employees' perception of organizational support plays a crucial role in determining how productive they are at work (Bonaiuto et al. 2022; Fleisher et al. 2011; Li et al. 2023). In this era, where machines are capable of handling almost all the possible tasks of humans, they can also predict their performance and productivity (Goumopoulos and Potha 2023). Machine learning is a subfield of artificial intelligence that employs rapid learning from training data and past experiences to predict events automatically without direct programming (Wardhani et al. 2022). The goal of machine learning is to mimic the human intellectual ability to solve complex problems and analyze them based on experience (Sarker 2022). Depending on the type of method, machine learning algorithms can be used to solve different problems in different industries. An appropriate machine learning algorithm aids in forecasting issues by utilizing a series of parameters when the subject matter necessitates prediction and analysis (Obiedat and Toubasi 2022). Utilizing physiological data gathered by wearable sensors, machine learning was used to measure the impact of construction workers' happiness on production in a variety of human resource domains and areas. Re-weighted instances in the dataset using a Random Forest Machine Learning classifier to ensure that each class received the same total weight—a technique for balancing the classes in the dataset (Santhose and Anisha 2023). Exploring machine learning techniques has proven to be most effective in staff recruitment and job evaluation (Pampouktsi et al. 2023).

The 21st century is witnessing a significant increase in advancements in artificial intelligence. This has resulted in a need for new approaches to utilizing digital technologies in municipal management (Kazakov et al. 2020). In India, urban areas with a population of more than one million are administered by the municipal sector, a local government body. Divisions or departments that are well-organized are how the municipal corporation does its job (Bari and Dey 2022). The services of the municipality include the Housing Board, the Education Department, the Electricity Department, and the Water Supply and Sewage Disposal Undertaking. Millions of people who receive services from each of these departments have been served by municipality staff, who are skilled and knowledgeable. The strength of municipalities' economy enables the functioning of various cities in many counties (Kokenova et al. 2020). Some of them are the United Kingdom, the United States, the Philippines, India, South Africa, and numerous other nations. These organizations around the world help in providing development, medical services, training, lodging, and transport by gathering local charges and controlling awards from the State government (Madumo 2012). Municipalities can play a key role in the country's economic development by creating a conducive environment for investment, innovation, and growth. The workers of the municipalities must be productive enough to achieve the desired target for the year. According to Ali and Anwar (2021) and Karthik and Rao (2022), various key factors such as training, leadership, workplace incentives, motivation, rewards, and working conditions affect productivity. Employee productivity is also affected by organizational culture in the municipality sector. Linking rewards to performance and establishing a welcoming environment are two of the effects (Hong and Zainal 2022). This study (Elaho and Odion 2022) generally assumes that working environment, responsibility, and manager support are related to the efficiency of representatives of business centers in the College of Benin Ugbowo grounds, Benin City. Another study (Razali et al. 2023) proposed a machine learning approach for predicting the actual productivity of garment workers in Bangladesh, with a focus on achieving the target production without difficulties. Additionally, this suggests that workplace productivity indicators such as workload and supervisor support are useful. Many municipalities' primary objectives are to increase employee productivity, particularly among those seeking transparency, accountability, corporate culture in local government management, and improved service to citizens (Ismajli et al. 2015). To boost employee productivity, the company needs to find the quickest and easiest method to predict employee productivity.

1.1. Gaps Covered in the Present Study

One of management's primary concerns in any service-providing sector is increasing employee output. However, despite its significance, there is a dearth of theoretical and empirical research on employee productivity in the literature.

Additionally, a predictive model will be constructed to assess worker productivity through the application of machine learning algorithms.

Apart from that, it will state a comparison between six different machine learning algorithms on the data set composed of municipality workers of Uttarakhand.

Also, no previous studies have evaluated the incentives of each worker while using 3D Scattered plots by using the Python library.

1.2. The Main Aim of the Study

Various research studies are focused on combining two or more classifiers and uncovering how the integration of various algorithms and techniques can add to the prediction. The three goals of this research are as follows:

To predict the productivity of municipality workers of Uttarakhand through the collected data set with the help of a comparison of six different algorithms.

1. Evaluating the difference between targeted productivity and the actual productivity of all the 12 different departments in the municipality;
2. To evaluate the degree of incentive provided by the department to each of their workers according to the amount of productivity generated by the worker during the year.

The undertaken research is planned into six major sections. In Section 1, the research problem is defined with the gaps in the present scenario. Section 2 includes the literature review of the latest research conducted in the context of analyzing productivity through machine learning. Section 3 includes the research methodology part of the paper explaining the data sampling, data description, pre-processing of data, identification of algorithm, graphs and statistics, confusion metrics, and development of the model. Section 4 contains the results and discussion part. Section 5 provides the discussion, followed by the conclusion in Section 6. Finally, the limitations of this work and the future scope of this research article are described.

2. Theoretical Background

2.1. Employee Productivity

Employee productivity in municipalities is influenced by various factors, including leadership styles, performance evaluation systems, organizational learning, and labor competencies. Implementing an effective performance evaluation system can create a favorable environment for increased productivity (Manu 2015). Organizational learning has been found to have a positive significant relationship with human resource productivity in municipalities (Nkambule 2023). To increase an organization's overall effectiveness and efficiency, it is crucial to make efficient and effective use of its human resources (Sulistyaningsih 2023). Productivity can also be used to describe a group of workers' overall performance (Massoudi and Hamdi 2017). Productivity can be broadly defined as the ratio of an input measure to an output measure (Sauermann 2023). Thus, workers' productivity could be measured as a ratio of an input, such as the number of hours worked or the cost of labor, to an output, such as sales or units produced. In addition to salaries, incentives are the additional direct wages that are received by workers and are proportional to work performance. The output produced in the daily task is used to measure the organization's or workplace employees' productivity. The purpose of performance appraisal is to determine the ability and skill of an employee to perform a task, which is objectively and regularly evaluated using benchmarks, whether past- or future-oriented (Clement and Gwaltu 2023). To increase employee productivity, businesses must, therefore, identify their strengths and weaknesses. Performance measurement systems are used in municipalities to assess employee productivity and motivation. These systems help in making critical trade-off decisions and program changes. The returns from performance measurement systems are viewed as worth the costs despite diminishing perceived contributions to individual worker productivity and morale concerns (Anakpo et al. 2023). The motivation of employees in local government is influenced by the process of performance assessment. Factors such as salary, professional advancement, the opportunity for promotion, work conditions, and the objective assessment of performance measurements are important motivators (Ibrahim and Cuadrado 2023). The key performance indicators (KPIs) can be used to assess managerial efficiency and competitiveness at the municipal level. The KPIs can be quantified and form a basis for evaluating the effectiveness and competitiveness of the municipal economy (Multan et al. 2023).

Traditionally, labor productivity is derived from the aggregation of firm-level indicators, such as value added per worker (Sauermann 2023). Workers' wages can be deciphered as a skewed relation to efficiency, assuming that the example of hard labor is true (Chau et al. 2022). Higher skill levels are often associated with higher wages, but higher wages can also be influenced by higher work efficiency, giving rise to the problem of reverse causality

(Sauermann 2023). Both work efficiency and wages have their inadequacies concerning surveying laborers' efficiency (Sheehan and Garavan 2022). In an idealized society, the productivity of every worker would be observable at every precise instance. However, the output is rarely discernible at an individual level with a reasonable cost, thereby rendering the computation of each person's productivity fundamentally unachievable (Sauermann 2023). Laborers keep up with similar absolute results by beginning before the day and investing more energy in each meeting to the detriment of spending more hours in the field with a similar complete compensation (LoPalo 2023). The temperature, productivity, and adaptability of workers, as well as evidence from the production of survey data, state that the components that influence efficiency will be proficiency, viability, and quality. According to (Zebua and Chakim 2023), there are two ways to measure productivity: operational productivity and financial productivity. Financial productivity measures use monetary units for inputs, whereas operational productivity is a physical measure of inputs and outputs expressed in physical units.

2.2. Machine Learning Prediction on Productivity

Machine learning models have been used to predict productivity in various industries, including oilfield development (Song et al. 2023), oil and gas extraction (Kim et al. 2023), and construction activities (Juszczyk 2023). These models utilize historical data and various algorithms to estimate productivity and make predictions. (Hassani et al. 2019) This study utilized four different ML calculations to foresee overall equipment effectiveness (OEE), an exhibition measure in assembling. These calculations were support-vector machines, improved support-vector machines (Utilizing Hereditary Calculations), XG Boost, and profound learning. Balla et al. (2021) directed a review that showed good outcomes in foreseeing worker efficiency, quite possibly of their generally significant hierarchical variable. Three characterization calculations were utilized in this review: Neural Network (NN), Random Forest (RF), and Linear Regression (RL). The fact that Random Forest has the lowest correlation coefficient and MAE and RMSE values suggests that it is exceptionally adaptable at predicting employee productivity. The predictions that Safelite Glass Corporation's shift to piece rates will result in an increase in variance in output across employees and a rise in average productivity are put to the test with a brand-new data set. The output per worker at Safelite increased by 44 percent because of productivity effects. This firm had chosen a sub-par pay framework, as benefits likewise expanded with the change (Mallick et al. 2021). An information examination and AI approach were utilized to foresee the sintering machine's efficiency. Modern information on sintering machine efficiency was gathered at an incorporated steel plant. A straight relapse and fake brain organization (ANN) model were created to foresee the efficiency of the machine involving the agglomerate constituents as model information sources.

Machine learning algorithms (Random Forest and Logistic regression) mat be used to enable store staff to set product prices and discounts based on consumer behavior (Mahoto et al. 2021). This model gave excellent results in predicting product prices. Data mining tools and decision tree techniques are used to build predictive models and study the effects of ensemble learning and decision tree techniques on improving performance prediction in assembly support systems (Sorostinean et al. 2021). The results show that the slope-enhanced decision tree outperforms all other decision tree-based methods. Machine learning-based strategies are used to identify the fundamental factors that affect productivity (Hui et al. 2023). Four AI approaches were evaluated, with Extra Tree producing the most significant safety factor. Creation list, development pressure, compelling porosity, all-out natural carbon, gas immersion, and shale thickness are believed to be the principal factors influencing shale yield. This study shows a typical match ratio between the planned and actual generation of three new wells, 92.3%, providing insight into the identification of broken wells supplied with water to improve productivity. The prediction of employee performance is crucial for human resource management in identifying the strengths and weaknesses of employees and making strategic decisions (Banu et al. 2020). The use of machine learning algorithms, such as XG Boost, has also been effective in estimating employee performance, especially when dealing with data from HR Information Systems (Kazakov et al. 2020). Machine learning has also been applied in municipal management to forecast key indicators of socio-economic development, demonstrating its potential in predicting productivity in a municipality.

3. Research Methodology

3.1. Data Sampling

This is a predictive model evaluation-based study. The end goal of this study was drawn from the productivity data of workers working in four major municipalities in Uttarakhand, India. Uttarakhand is a developing state of India. Activities such as smart city projects, sewage treatment, sanitation, public facilities, social welfare, infrastructure development, urban planning, sports and leisure facilities, sanitation, and waste disposal are carried out by municipalities within the state for the smooth functioning of the cities. The total population was taken into consideration for further analysis and to calculate the genuine effectiveness and efficiency of the municipality's workers (Table 1). The data of 1098 respondents were extracted from the sources of four different municipalities of Uttarakhand, India. The total number of workers in the first municipality corporation is 275; the second corporation has 266, the third has 285, and the fourth municipality consists of 272 workers.

Table 1. Flow chart of research methodology.

No. of Steps	Description of Research Methodology
1	A total population of 1098 was extracted from the 4 different municipalities.
2	Six algorithms were identified through lazy prediction and applied to the data set.
3	The data were studied thoroughly by the authors for further pre-processing through Jupyter Notebook in Python language. In the preprocessing part, the data are organized (numbering each department, segregating the workers department-wise, handling missing values).
4	Further correlation analysis was performed to find out the correlation between the variables and to clearly understand the data in and out.
5	Fourthly, the data were split up into two parts: training and testing. Training consisted of 879, and testing contained 219.
6	The model was trained, and correlation analysis was applied to predict the required results.
7	Lastly, with the help of the results and the evaluation process of the model techniques like MSE and R Squared, a predictive model was developed.

3.2. Dataset Description

This dataset description provided in Table 2 incorporates a significantly detailed description of the attribution of the municipality of Uttarakhand. In the dataset, names and values were given to the properties to keep up with the secrecy of the information. Workers working under 12 different departments of four municipalities were undertaken in the data set. Every department has been indicated with the respective number, as explained in Table 3. Following information like department, targeted productivity, SMV, WIP, overtime, incentive, and actual productivity were identified from the provided data set. The data were in a jumbled form. Further, it was segregated department-wise with the respective number of workers working in the municipalities.

Evaluation of the Number of workers in every department:

Table 3 contains all the 12 departments of the municipal corporation, which were taken into consideration for the survey with the number of workers working in the different departments. The data were provided in mixed form, which was further segregated according to the department. Thus, by adding the total number of workers of each department individually, with the help of Microsoft Excel, the total count of workers who are all providing services in the urban areas was finally provided. The highest number of workers are in the education department of the municipality and the lowest number of workers are in the Project Implementation Unit.

Table 2. Data description.

S. No.	Attribution	Description
1	Department Number	It ranges from 1–12.
2	Targeted productivity	Productivity targets are set by the department for each team for each quarter.
3	SMV	Standard Minute Value is the allocated time for a task.
4	WIP	Work in progress. Includes the number of unfinished works for each department.
5	Overtime	Represents the amount of overtime by each team in minutes.
6	Incentive	Represents the level of financial incentive that enables or motivates a particular course of action.
7	Actual productivity:	Percentage of actual productivity provided by workers. It varies from 0 to 1.

Table 3. The number of workers in each department of the municipality.

Department No.	Department Name	No. of Workers (Data from Each Dept)
1.	Public work department	90
2.	Property tax department	99
3.	Health department	88
4.	Street light department	94
5.	IT department	85
6.	Sanitation department	91
7.	Birth/Death Certificate department	86
8.	Education department	101
9.	Disaster management	96
10.	Election department	93
11.	Project Implementation Unit (PIU) CELL	80
12.	Postal mail department	95

3.3. Identification of Algorithms through Lazy Predict Python Library

Lazy predict is an essential Python library for vision rendering projects. It is a simple and efficient language that makes creating advanced presentation projects easy and fast. It is a Python library that provides easy and efficient ways to generate forecasts and is very easy to use and install in the system. Lazy predict is distributed under the MIT license and is an open-source library. Using lagged prediction, 42 different algorithms were identified, of which the first 6 were considered for further analysis based on R Squared, adjusted R Squared, and RMSE (root mean squared error). According to the lazy predict library, among all the favorable algorithms, Gradient Boosting Regressor works the best on the provided data set of municipality as the adjusted R Squared is 0.37 and R Squared is 0.39, as displayed in Table 4.

Table 4. Results of identified algorithms.

S. No.	Model	Adjusted R Squared	R Squared	RMSE	Time Taken
1	Gradient Boosting Regressor	0.37	0.39	0.14	0.09
2	LGBM Regressor	0.33	0.35	0.15	0.07
3	Hist Gradient Boosting Regressor	0.33	0.35	0.15	0.48
4	Random Forest Regressor	0.2	0.22	0.16	0.31
5	Ada-boost Algorithm	0.17	0.2	0.16	0.05
6	Xg-Boost Regressor	0.11	0.14	0.17	0.1

3.4. Preprocess of Data

The data were studied thoroughly by the authors, for further pre-processing through Jupyter Notebook in Python language. In the preprocessing part of the analysis, the data are organized (numbering each department, segregating the workers department-wise, handling missing values). Firstly, the predominant libraries were imported into the software, and the data were loaded. Each department was assigned a serial number. There were 22 missing values in the data set in the WIP column. It was filled with the missing data techniques, and they all were replaced with their mean value. On the given set of data, correlation analysis was applied to check the correlation between the variables. Further, the data were split into two different sets, i.e., training and testing. The training set contained data numbering 879, and the testing set of data contained 219 as the ideal ratio in machine learning to split the data, which is 80% in training and 20% in testing. With this, a 3D Scatter plot graph was also made to show the highest and lowest received incentives.

3.5. Graphs and Statistics

3.5.1. Targeted and Actual Productivity

Figure 1 shows the total actual and targeted productivity of every department. A clear difference can be seen between targeted productivity and the actual productivity of the department. The data set had already provided the individual workers targeted and actual productivity. Generally, the management of these four municipalities identifies key performance indicators that align with the overall goals and objectives of the municipality. The KPIs are measurable, specific, and relevant to the employee's role as they help in establishing performance metrics to quantify the output and quality of work (Jin et al. 2023). This includes quantitative measures such as the number of tasks completed, time taken, (SMV) Standard Minute Value, (WIP) work in progress, accuracy, overtime, and efficiency. Data were provided in a jumbled form that was firstly segregated according to the department. Further, with the help of Microsoft Excel, the target productivity and actual productivity of every worker given in the data were added up to evaluate the total actual and targeted productivity of each department. With the help of Figure 1, an analysis can be drawn as to which department has achieved more or less than the targeted work. According to the overall performance, Department of Public Work, Property Tax, Health, Streetlight, and IT have achieved more than the targeted productivity, and the rest have achieved less in comparison to the targeted productivity.

3.5.2. Evaluation of Incentive Based on Productivity

The 3D Scatter plot provided below in Figure 2 depicts the level of incentive provided by the department to each of their workers according to the amount of productivity generated by the worker during the year. The Scatter plot is made using the Python library. According to Figure 2, the targeted productivity of the worker from the IT department of the municipality was 0.6, and its actual productivity was 0.4151724; accordingly, no incentive was received during the year.

Similarly, in Figure 3, the targeted productivity of a worker from the same department was 0.6, and its actual productivity was 0.8643426; accordingly, they received an incentive of INR 2880. From the following Scatter plot, we can easily identify the level of incentive received based on the performance and productivity of a worker.

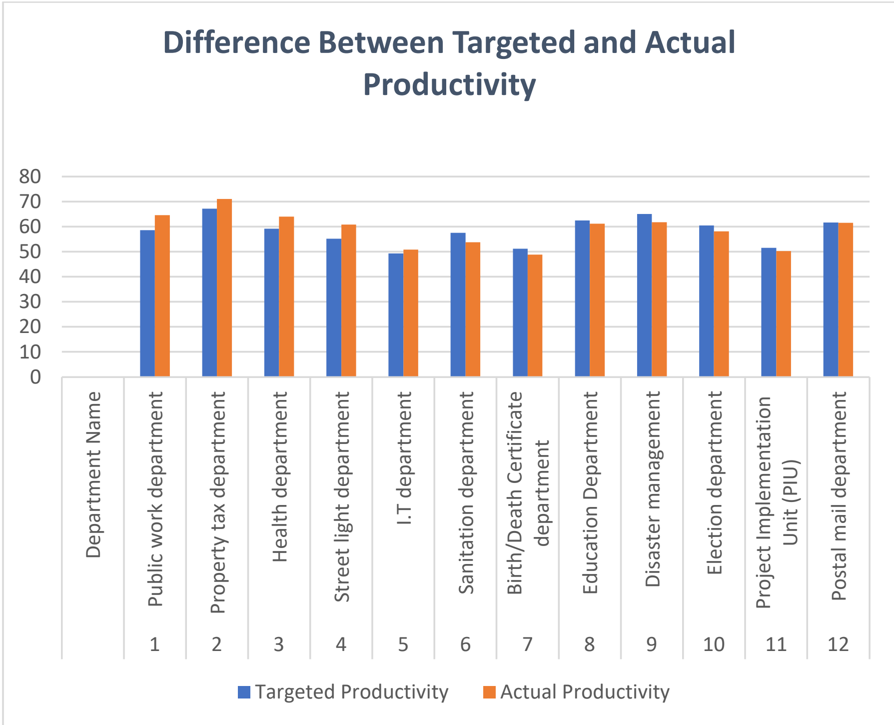


Figure 1. The graphical representation of actual productivity achieved in comparison to the targeted productivity.

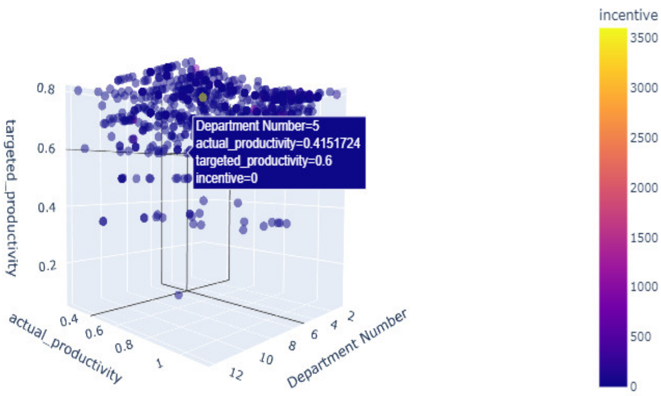


Figure 2. The lowest incentive received by an employee from department 5.

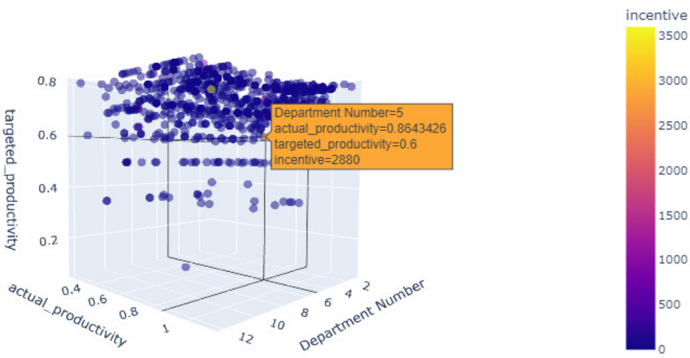


Figure 3. The highest incentive received by employees from department 5.

3.5.3. Correlation Matrix

By using the data, we looked at the correlation between the variables of the study by using the Pearson correlation coefficient (Okpara et al. 2023). The highest correlation between the SMV and the overtime was discovered, with a correlation value of 0.91 displayed in Figure 4.

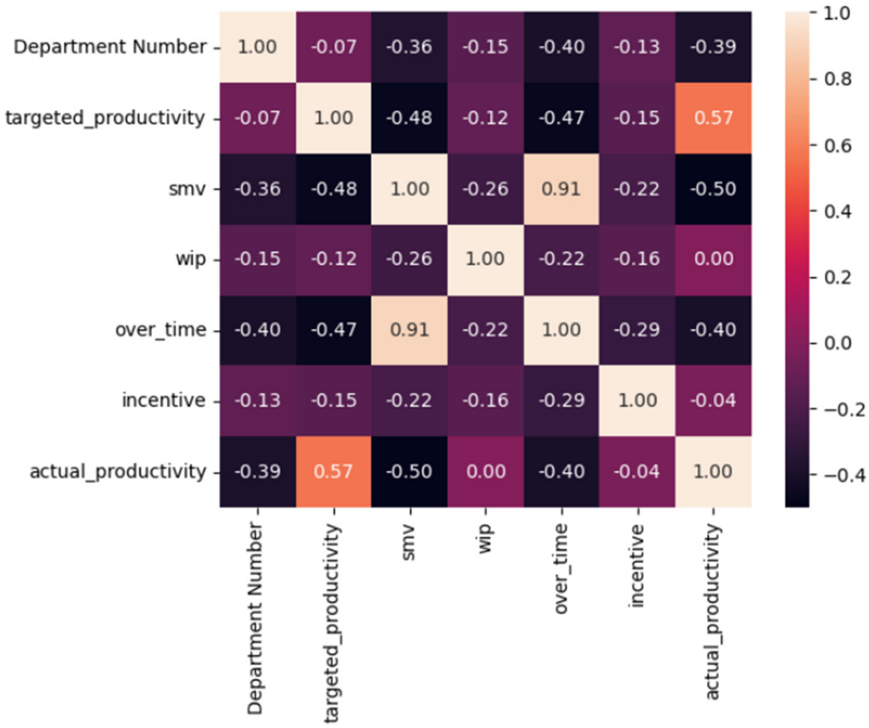
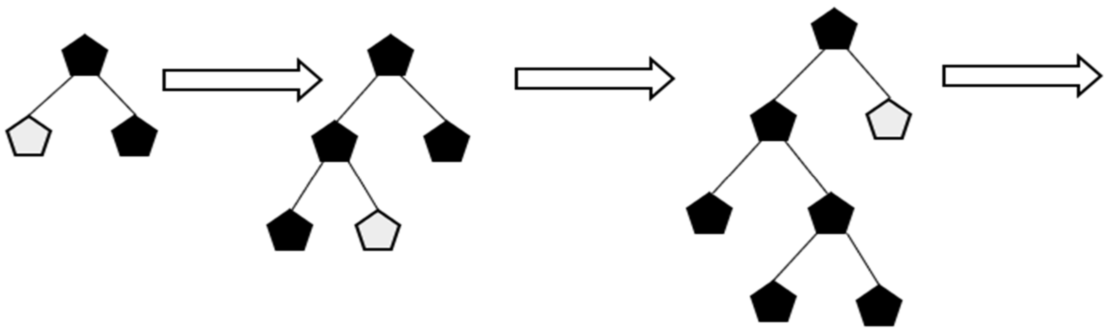


Figure 4. Correlation matrix using heat map of classifiers.

3.6. Development of the Model

Hist Gradient Boosting Regressor—Histogram-based gradient boosting is one method for training faster decision trees that has been utilized in the gradient boosting ensemble. It is a statistical framework that greatly enhances the technique's capabilities by permitting the use of arbitrary loss functions and treating the training process as an additive model. Therefore, gradient-boosting ensembles are the preferred method for most structured predictive modeling tasks, such as tabular data. The creation of further set trees can be considerably expedited by discretizing continuous input variables into several hundred discrete values (Brownlee 2021).

LGBM Regressor—LightGBM is an inclination-helping system because of choice trees that work on model productivity while decreasing memory use (Figure 5). It utilizes two creative methodologies: Selective Component Packaging (EFB) and Slope-based One Side Examining (GOSS). These arrangements address the shortcomings of the calculation based on the histogram that forms the basis of all GBDT (Slope Supporting Choice Tree) frameworks. The two strategies of GOSS and EFB explained below serve as a frame for the highlights of the LightGBM Calculation. They work together to ensure that the model functions effectively and that it has an advantage over elective GBDT structures. LightGBM divides the tree into leaves instead of constructing it level by level. The leaf with the greatest delta development catastrophe is selected. When considering a particular leaf, leaf-wise computation is less susceptible compared to level-wise calculation. Building a tree leaf-by-leaf may increase the model's complexity and result in overfitting when dealing with small datasets.



LightGBM Leaf-wise

Figure 5. The architecture of LightBGM. Source: (Mandot 2017; Hui et al. 2023).

Gradient Boosting Regressor—A gradient-boosting machine (GBM) is a machine learning algorithm for boosting weak learners or decision trees into stronger learners (Kuhn and Johnson 2013). The regression model also keeps adding a new decision tree to the old model for each iteration to lower error rates and improve performance. For the forecasting model, the GBM would construct a regression model that could calculate employee productivity based on its correlation with other factors (Park et al. 2023). Gradient boosting is a technique for enhancing the quality of machine learning models when their predictability is low. In every learning process, gradient-boosted regression (GBR), an iterative technique, maximizes a model's predictive power. By handling outliers and missing values, it can help the model become more general. Gradient boosting is a technique used to boost a weak learner, or the difference between predicted and actual target values, to enhance the performance of a predictive model and optimize the loss function. Training a decision tree is how this algorithm works (Algorithm 1). It weighs each tree and categorizes them based on their difficulty. Figure 6 shows Gradient Boost uses an iterative process to combine various weak models into a stronger model while minimizing bias error (Rahman and Nisher 2023). Even when dealing with classification problems, gradient boosting always makes use of regression trees (Johansson n.d.).

Algorithm 1. Algorithm function of Gradient Boosting.

Input: a differentiable loss function with several iterations M.
1. Begin the model with a constant value:
2. For m ranging from 1 to M:
Calculate the so-called pseudo-residuals:
• Fit a base learner (or weak learner, such as a tree) that is closed under scaling to pseudo-residuals, i.e., train it with the training set. (Johansson n.d.)
• Determine the multiplier by solving the one-dimensional optimization problem:
• Revise the model:
3. Productivity

The singular learning calculation in this review uses one of the most frequently used DTs, namely, the truck. The following four stages, taken together, represent how the GBRT is carried out:

(1) Gather and interact with the information, such as by adjusting the info/yield factors and gathering the preparation/testing datasets;
(2) Train the relapse model with the GBRT using the training dataset;
(3) Verify the prepared model with the testing dataset;
(4) Apply the model to real-world problems.

Random Forest Regressor—RFR divides the parameter iteratively using a series of binary splits in Figure 7. Each of these splits is correlated with the value of a specific predictor grid that maximizes the variations in the "tree's" branches. One decision tree consists of one split and all its related branches. Each branch is made up of a random subset of nodes that stand in for specific predictors. Each predictor node has many potential predictors associated with it, and it is at these nodes that a decision to split the branch further and add two new predictors is made at random. The process is repeated until there are no longer any splits, leaving only terminal nodes or "leaves". Typically, the RFR will keep performing binary splits until only one predictor is found on a leaf. The overfitting of the prediction may result from this. However, by using a minimum-samples-per-leaf approach, we lessen the chance that our prediction will be overfit. The predictands of the terminal node (or "leaf"), which must number the predetermined minimum samples per leaf, are averaged to produce a single tree prediction value. By averaging the outcomes from every tree in the "forest", the overall prediction is calculated. RFR cannot predict outside of the range of the direct observations within the original data set because the algorithm can only make predictions based on the data set with which it was initially trained Graw et al. (2021) (refer to Figure 7).

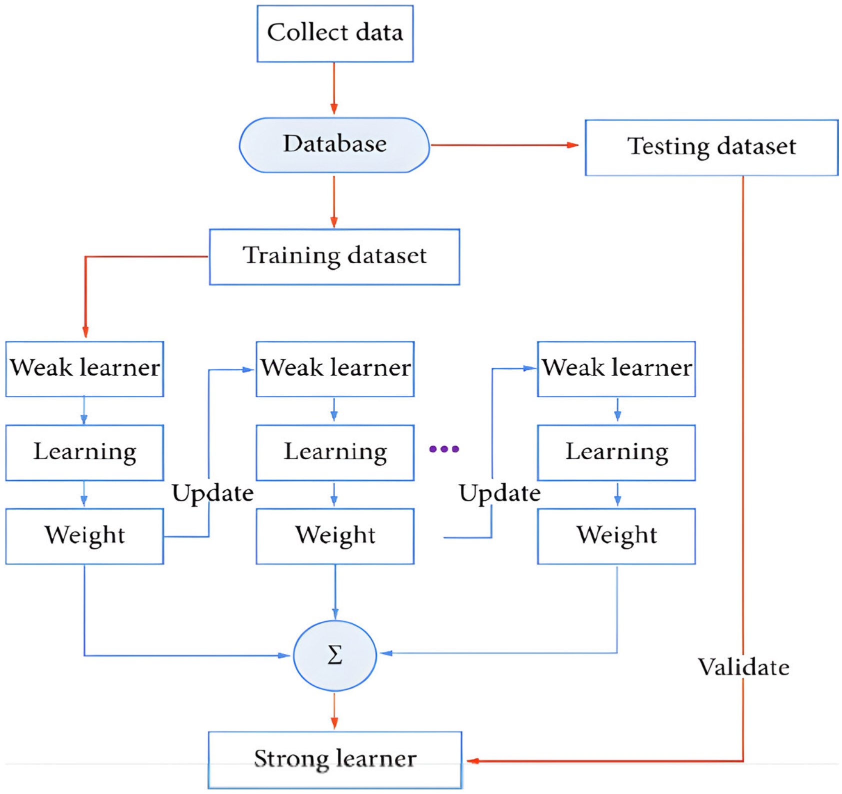


Figure 6. The procedure of gradient boosting. Source—Feng and Fu (2020).

Using the Random Forest regressor to make a prediction, as shown in Figure 7. Every brown node is a distinct predictor with a unique set of predictors. The leaves are represented by the green nodes, and there are a few associated predictors. The leaf node where the minimum samples per leaf threshold is met is where the prediction is made. Each tree's prediction path is shown by a series of red arrows.

Ada Boost Algorithm—Ada Boost is an ensemble of many weak learner decision trees that outperforms random guessing. The adaptive AdaBoost method, on the other hand, transmits the gradient of previous trees to succeeding trees to lower the error of the prior tree. As a result, the subsequent learning of trees at each step develops a strong learner. The weighted average of the forecasts made by each tree serves as the final forecast. AdaBoost is more resistant to outliers and noisy data due to its high adaptability, which is a crucial requirement in our case. Additionally, the algorithm is designed to function in a way that future trees are fed the knowledge gained by earlier trees (Algorithm 2), allowing them to concentrate only on training samples that are challenging to predict; Freund and Schapire (1997); Patil et al. (2018).

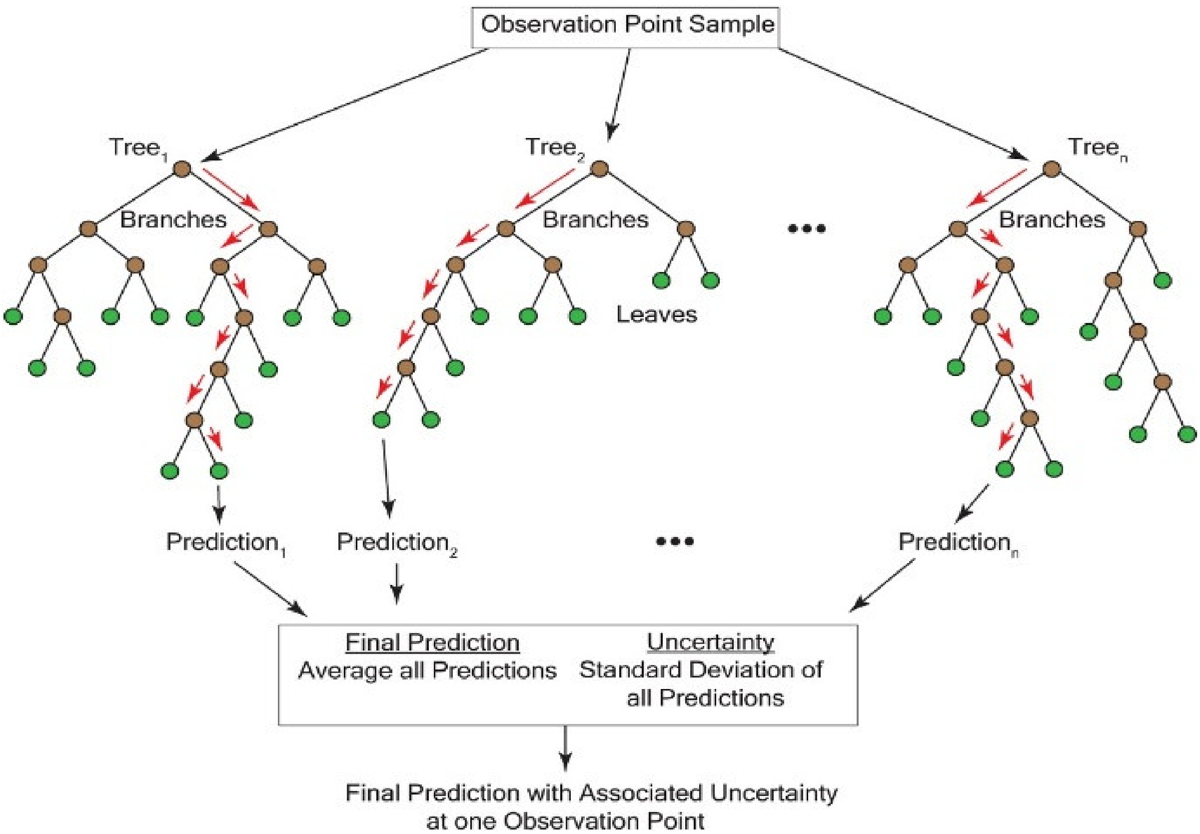


Figure 7. Procedures for making a prediction using Random Forest regressor. Source—Graw et al. 2021.

Algorithm 2. Algorithm function of Ada Boost.

Algorithm

1. Consider a training set (x_i, y_i), initialize the weights $w_{1,1}........w_{n,1}$ to $(1/n)$ and initialize the number of weak learners h

2. For g in 1 to G

i. Compute the error of each learner by using the square loss function

$$\mathrm{E} = \mathrm{L}(\mathrm{f}(\mathrm{x_i}), \mathrm{y_i}) \tag{1}$$

ii. Select the weak learner $\mathrm{h}_\mathrm{g}^\mathrm{i}$ which minimizes the error.

iii. Add it to the tree-building algorithm

$$\mathrm{Fg}(\mathrm{x}) = \mathrm{Fg} - 1(\mathrm{x}) + \mathrm{A} * \mathrm{h}_\mathrm{g}^\mathrm{i} \tag{2}$$

where A is the learning rate.

iv. Update the weights $\mathrm{w}_{\mathrm{i},1........\mathrm{w}_{\mathrm{n},1}}$.

3. Fg(x) is the final prediction. Freund and Schapire (1997)

$$\mathrm{Fn}(\mathrm{x}) = \mathrm{Fm} - 1(\mathrm{x}) + \mathrm{argminh} \sum \mathrm{ni} = 1\mathrm{L}(\mathrm{yi}, \mathrm{Fm} - 1(\mathrm{xi}) + \mathrm{h}(\mathrm{xi})) \tag{3}$$

where Fn(x) is the overall model, $\mathrm{Fm} - 1(\mathrm{x})$ is the overall obtained in the previous round, yi is the prediction result of the i-th tree, and h(xi) is the newly added tree Freund and Schapire (1997) (refer to Figure 8).

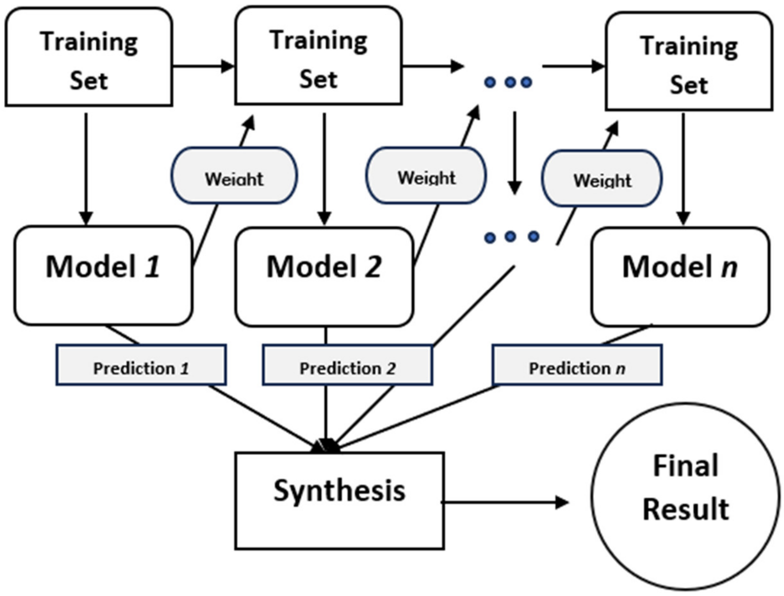


Figure 8. AdaBoost algorithm calculation process.

XG Boost Regressor—XG Boost is a distributed gradient boosting library designed to be very effective, versatile, and portable. It implements machine learning methods using the Gradient Boosting framework. It provides parallel tree boosting to tackle a wide range of data science issues rapidly and correctly. Gradient-boosted decision trees (GBM) have an extension called XG Boost, which was created specifically to increase speed and effectiveness. When compared to the other benchmarked implementations from R, Python, and Spark, XG Boost was almost always quicker. It was also quicker when compared to the other algorithms. The XG Boost gradient boosting method sequentially ensembles decision trees using a gradient descent optimization algorithm to reduce model error; Chen and Guestrin (2016); Zamani Joharestani et al. (2019); Shwartz-Ziv and Armon (2022) (refer to Figure 9).

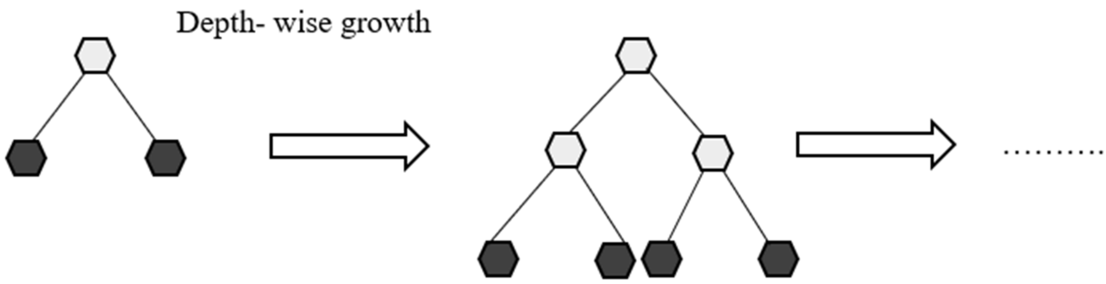


Figure 9. The architecture of XG Boost. Source: Nadeem (2021).

4. Results

Evaluation of the Model

Now that a predictive model through a machine learning algorithm was built, the evaluation process of the model techniques MSE (Mean Squared Error) and R Squared Error is used to analyze and evaluate its accuracy.

MSE—In statistics, an estimator's Mean Squared Error (MSE) or mean squared deviation (MSD) measures the average of the squares of the errors, that is, the average squared difference between the estimated and actual values (Melibaev et al. 2023). The expected value of squared error loss is represented by MSE, a risk function.

$$\mathrm{MSE} = \frac{1}{n}\sum_{I=1}^{N}\left(X_i - \hat{X}_i\right)^2 \tag{4}$$

n = number of data points
X_i = observed values
$\hat{X}_i$ = predicted values

R Squared—The coefficient of determination, abbreviated as R^2 or r^2 and pronounced "R squared" in statistics, is the fraction of the variation in the dependent variable that is predicted from the independent variable (Piepho 2023).

$$R^2 = 1 - \frac{RSS}{TSS}. \quad (5)$$

R^2 = Coefficient of determination;
RSS = Sum of squares of residuals;
TSS = Total sum of the squares.

With the help of Scikit Learn, we call the library of MSE and R Squared.

This examination focused on accomplishing the most noteworthy precision with R Squared and (MSE) Mean Squared Error for predicting workers' efficiency. Six algorithms, specifically XG Boost, Hist Gradient Boosting, Ada Boost, LGBM, Random Forest, and Gradient Boosting, are contrasted with one another. The exploration of the study focuses on accomplishing the most noteworthy R Squared with negligible upsides of MSE for anticipating municipality laborers' efficiency. The R^2 and MSE provided insights into both the proportion of variance explained and the magnitude of errors (Hayduk 2006). We have not taken MAE as it is less sensitive to outliers; instead, we used MSE because it does not square the errors as it represents the average absolute difference between predicted and actual values (Hodson 2022). Similarly, we have not taken RMSE to compare the performance of the six different algorithms (Figure 10), as performed by lazy predict earlier in methodology, because the same units of RMSE are the square root of MSE and have the advantage of having the same units as the target variable (Chai and Draxler 2014).

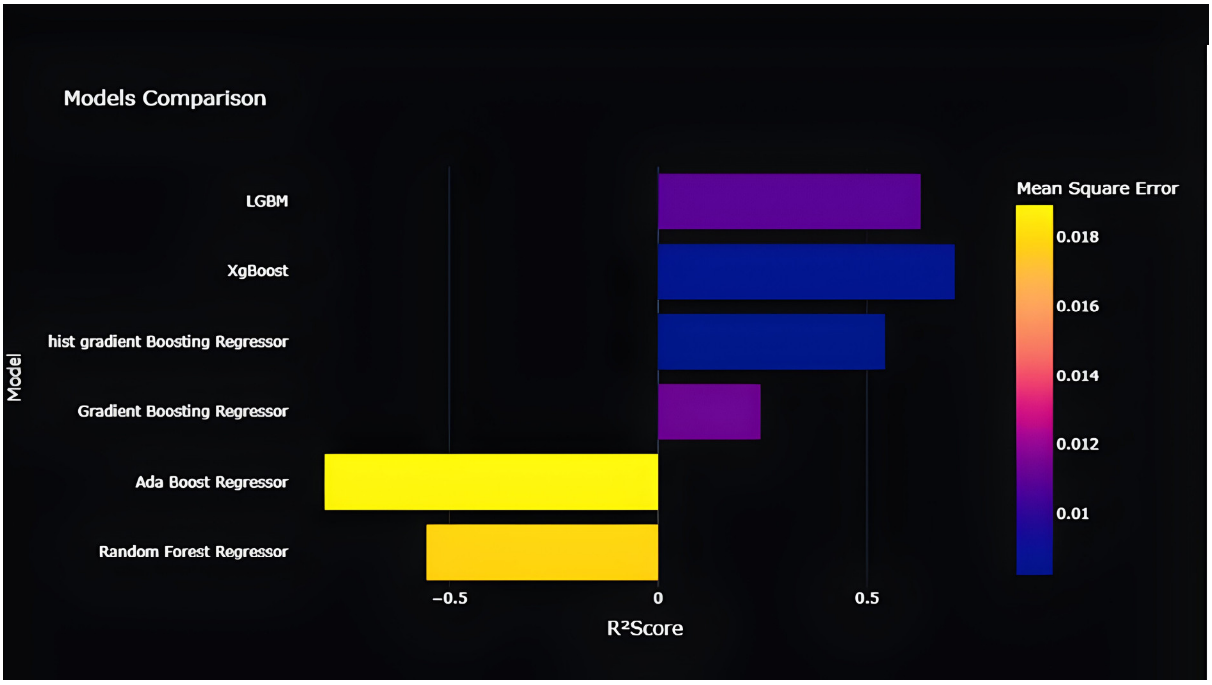


Figure 10. Performance model comparison of six different algorithms.

All characterization and relapse calculations, first and foremost, have been applied to the municipal efficiency dataset, and the model through the assessment procedures, which are MSE and R-Square qualities, was recorded (refer to Table 5). The most elevated

R Squared esteem is 0.71, and the negligible MSE is worth 0.01 separately in the XG Boost help calculation. The least R Squared esteem is 0.80, and the MSE is worth 0.02 individually in the Ada Boost Regressor. Figure 10 shows an outline and envisioned portrayal of the R Squared and MSE results. After auditing every calculation and their outcome, which is displayed in the diagram, it can be seen that XG Boost performs perfectly well in the dataset with exceedingly significant elements.

Table 5. Performance evaluation of model.

Model	R Squared	MSE (Mean Squared Error)
XG Boost	0.71	0.01
LGBM	0.63	0.01
Hist Gradient Boosting Regressor	0.54	0.01
Gradient Boosting Regressor	0.25	0.01
Random Forest Regressor	−0.55	0.02
Ada Boost Regressor	−0.80	0.02

5. Discussion

Goumopoulos and Potha (2023) and Boyacı et al. (2023) indicated that machines are capable of handling almost all the possible tasks of human beings and can also predict their performance and productivity. Hassani et al. (2019) and Balla et al. (2021) stated how productivity can be evaluated or predicted through various machine learning algorithms. In a wider view, this paper predicted a model that can be used by various other municipalities with the same set of variables to calculate the productivity of employees or any department (Razali et al. 2023). The current study contributes a predictive machine learning model with a set of variables like Department Number, targeted productivity, Standard Minute Value, work in progress, overtime, amount of financial incentive, and actual productivity. Further, with the help of the lazy predict library, this paper identified the six sets of algorithms among them. It also predicted that Gradient Boosting Regressor works the best. The data provided by the sources were organized well to find out the total number of workers working in each department collectively in four major municipalities. Also, the sum of the targeted and actual productivity of 12 departments was evaluated using Microsoft Excel. Eventually, the difference between total target and actual productivity was also identified. With the help of correlation analysis, the model predicted by the auditing comparison in Table 5 and the calculation and its outcome, it is seen that XG Boost performs perfectly well in the dataset with exceedingly significant elements. Discussing the analysis of the incentive for each worker can be easily identified with the help of a 3-D Scatter plot. Lastly, the correlation matrix is drawn by using a heat map of classifiers that shows the correlation between the factors using the Pearson correlation coefficient (Okpara et al. 2023). The highest correlation can be seen between the SMV and the overtime with a correlation value of 0.91.

6. Conclusions

In the ever-evolving landscape of organizational management, the quest to enhance employee productivity led to the exploration of innovative approaches, with machine learning (ML) emerging as a promising tool. This paper aims to predict the productivity of municipality workers of Uttarakhand state in India. The data set includes targeted productivity, work in progress, Standard Minute Value, overtime, incentive, and actual productivity. According to the lazy predict library, among all the favorable algorithms, Gradient Boosting Regressor works the best on the provided data set of municipality as the adjusted R Squared is 0.37 and the R Squared is 0.39. Further, correlation analysis was applied, where the data were split into training and testing. A 3D Scatter plot and correlation matrix were also drawn. After applying the exploratory factor analysis, a performance evaluation result was drawn which identifies that the XG Boost algorithm works well in the dataset with the values of MSE 0.01 and R Squared 0.71. Other than this, we calculated the total number of workers in 12 different departments of four municipalities. This paper also successfully analyzed the difference between the targeted and actual productivity of 12 different departments of the municipality in Uttarakhand. Results depict that the Department of Public Work, Property Tax, Health, Streetlight, and IT achieved more than the targeted productivity, and the rest achieved less in comparison to the targeted productivity. Municipalities or any other sector can use this model to predict productivity and easily find out the most productive employee and their incentive with the help of a 3D Scatter plot.

7. Future Implications and Limitations of the Study

The limitation of the present study can be added to future research. Firstly, many factors such as salary, presentism, absenteeism, and rewards that were not taken into consideration can be used for further research in municipalities or any other service sector worldwide. Secondly, a similar kind of study can be conducted in other countries as well, using the same model in various industries, companies, or any public or private organization for evaluating performance- or productivity-enhancing factors. Secondly, since this study focused on a small sample size of only four municipalities, scholars can take up the rest of the municipalities in the Uttarakhand state of India for the analysis of the overall productivity of each department to carry forward and add significant findings to the present study. Lastly, this study is limited to the analysis of data through machine learning algorithms; so, for more advanced research, one can analyze their data set by using deep learning algorithm technology.

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