

Final Project Report On

Machine Learning Approach for Employee Performance Prediction

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Introduction:Employee Performance Prediction Using Machine Learning

Employee performance plays a vital role in the success of any organization. Predicting performance accurately can help in better talent management, training, and decisionmaking. This project aims to develop a machine learning model that can predict employee performance based on various features such as experience, working hours, education, department, and other relevant factors. By analyzing historical data, the model identifies key patterns and provides insights into employee efficiency, enabling organizations to take proactive steps in workforce planning and productivity improvement.

Project Overview:

This project focuses on building a machine learning model to predict employee performance using historical data. The dataset includes features such as department, education level, experience, working hours, and productivity metrics.

he final model helps identify high-performing employees and potential under performers, supporting HR in making data-driven decisions for performance management and resource allocation.

Objective:

The main objective of this project is to develop a machine learning-based system that can accurately predict employee performance using relevant features from workplace data. This includes:

1. Identifying key factors that influence employee productivity.
2. Building and evaluating predictive models using various machine learning algorithms.
3. Supporting HR and management in making informed decisions regarding promotions, training, and workforce optimization.
4. Enhancing organizational efficiency by proactively identifying performance trends and potential issues.

Project Initialization and Planning Phase

Date	25-july-2025
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Team ID	SI-30537-1753978762
Project Name	Machine Learning Approach for Employee Performance Prediction
Maximum Marks	3 Marks

Define Problem Statements (Customer Problem Statement Template):

In modern organizations, employee performance plays a crucial role in overall productivity and business success. However, traditional performance appraisal methods are often subjective, time-consuming, and may not reflect the true capabilities or potential of employees. This creates challenges in talent management, reward distribution, and workforce planning. To address this, we aim to develop a Machine Learning-based Employee Performance Prediction Model that can analyze various employee-related factors such as work experience, department, education, training hours, previous evaluation scores, KPIs, and other relevant features to accurately predict performance levels.

The goal of this project is to assist HR departments in making data-driven decisions regarding promotions, appraisals, and employee development by providing objective performance predictions. This model should also help identify employees at risk of underperforming, enabling early interventions.

Problem Statement (PS)	I am (HR of XYZ company)	I'm trying to	But	Because	which makes me feel

PS-1	an HR in a xyz Company	predict employee performance	current methods are slow and biased	they depend on manual, subjective reviews	Optimistic about employee Performance
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Initial Project Planning Report

Date	25-july-2025
Team ID	SI-30537-1753978762
Project Name	Machine Learning Approach for Employee Performance Prediction
Maximum Marks	4 Marks

Product Backlog, In-Review, and Tasks

Task and Progress	Functional Requirement	Task Number	User Story / Task	Priority	starting Date
1	Data Collection	TSK-346104	Download the dataset	High	25-July-2025
2.	Visualization And Analysis of dataset	TSK-346105	Import The Libraries	High	26-July-2025

		TSK-346106	Read The Dataset	Medium	26-July-2025
		TSK-346107	Correlation Analysis	High	30-July-2025
		TSK-346108	Descriptive	High	30-July-2025

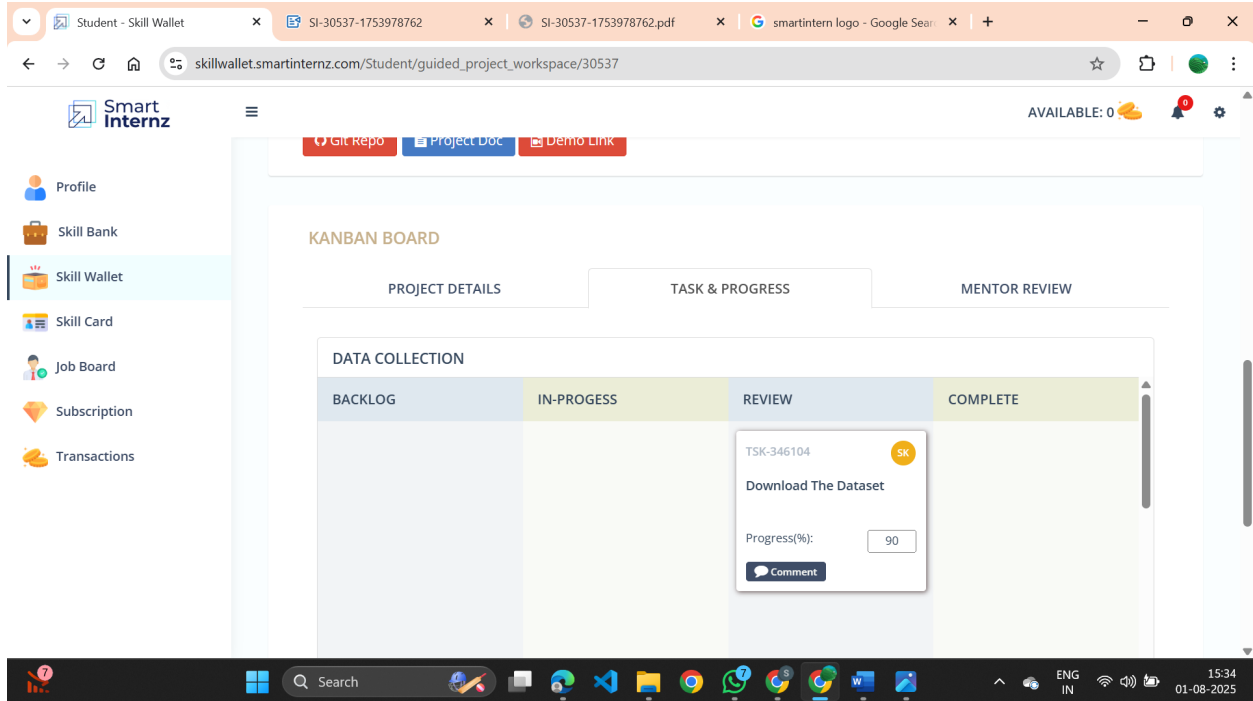
			Analysis		
3.	Data Preprocessing	TSK-346109	Checking For Null values	Medium	30-July-2025
		TSK-346110	Handling Date & Department Column	High	30-July-2025
		TSK-346111	Handling Categorical Data	High	30-July-2025

		TSK-346112	Splitting Into Train & test mode	High	30-July-2025
4.	Model Building	TSK-346113	Linear Regression Model	High	30-July-2025
		TSK-346114	Random Forest Model	High	30-July-2025
		TSK-346115	XgBoost Model	High	30-July-2025

		TSK-346116	Compare The Model	High	30-July-2025
		TSK-346117	Evaluation Performance of the model and saving the model	High	30-July-2025

5.	Application	TSK-346118	Building Html	High	30-July-2025
	Building		Pages		
		TSK-346119	Build Python Code	High	30-July-2025
		TSK-346120	Run The Application	High	30-July-2025
		TSK-346121	Output	High	30-July-2025

SCREENSHOTS



The screenshot displays the Smart Internz Skill Wallet interface. The browser address bar shows the URL: `skillwallet.smartinternz.com/Student/guided_project_workspace/30537`. The interface includes a sidebar with navigation options: Profile, Skill Bank, Skill Wallet (highlighted), Skill Card, Job Board, Subscription, and Transactions. The main content area is titled "KANBAN BOARD" and features three tabs: PROJECT DETAILS, TASK & PROGRESS (selected), and MENTOR REVIEW. Under the TASK & PROGRESS tab, there is a "DATA COLLECTION" section with a Kanban board. The board has four columns: BACKLOG, IN-PROGRESS, REVIEW, and COMPLETE. A task card is visible in the IN-PROGRESS column, titled "Download The Dataset" with ID "TSK-346104". The task card shows a progress bar at 90% and a "Comment" button. The bottom of the screen shows a Windows taskbar with the date and time: 15:34, 01-08-2025.

Student - Skill Wallet | SI-30537-1753978762 | SI-30537-1753978762.pdf | smartinternz logo - Google Search | +

skillwallet.smartinternz.com/Student/guided_project_workspace/30537

Smart Internz

AVAILABLE: 0

PROJECT DETAILS | TASK & PROGRESS | MENTOR REVIEW

DATA COLLECTION

VISUALIZING AND ANALYZING THE DATA

BACKLOG	IN-PROGRESS	REVIEW	COMPLETE
		<div>TSK-346105</div> <div>Importing The Libraries</div> <div>Progress(%): 90</div> <div>Comment</div>	
		<div>TSK-346106</div> <div>Read The Dataset</div> <div>Progress(%): 90</div> <div>Comment</div>	

Windows Taskbar: Search, File Explorer, Edge, Word, PowerPoint, Teams, OneDrive, 15:35 01-08-2025

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skillwallet.smartinternz.com/Student/guided_project_workspace/30537

Smart Internz

AVAILABLE: 0

PROJECT DETAILS | TASK & PROGRESS | MENTOR REVIEW

DATA COLLECTION

VISUALIZING AND ANALYZING THE DATA

DATA PRE-PROCESSING

BACKLOG	IN-PROGRESS	REVIEW	COMPLETE
		<div>TSK-346109</div> <div>Checking For Null Values</div> <div>Progress(%): 90</div> <div>Comment</div>	
		<div>TSK-346110</div> <div>Handling Date & Department Column</div> <div>Progress(%): 90</div> <div>Comment</div>	

Windows Taskbar: Search, File Explorer, Edge, Word, PowerPoint, Teams, OneDrive, 15:39 01-08-2025

Student - Skill Wallet x SI-30537-1753978762 x SI-30537-1753978762.pdf x smartinternz logo - Google Search x +

skillwallet.smartinternz.com/Student/guided_project_workspace/30537

Smart Internz AVAILABLE: 0

- Profile
- Skill Bank
- Skill Wallet
- Skill Card
- Job Board
- Subscription
- Transactions

DATA COLLECTION

VISUALIZING AND ANALYZING THE DATA

DATA PRE-PROCESSING

MODEL BUILDING

BACKLOG	IN-PROGRESS	REVIEW	COMPLETE
		<div>TSK-346113 SK</div> <div>Linear Regression Model</div> <div>Progress(%): 90</div> <div>Comment</div>	
		<div>TSK-346114 SK</div> <div>Random Forest Model</div> <div>Progress(%): 00</div> <div></div>	

15:39 01-08-2025

Student - Skill Wallet | SI-30537-1753978762 | SI-30537-1753978762.pdf | smartinternz logo - Google Search | +

skillwallet.smartinternz.com/Student/guided_project_workspace/30537

Smart Internz

AVAILABLE: 0

APPLICATION BUILDING

BACKLOG	IN-PROGRESS	REVIEW	COMPLETE
		<div><p>TSK-346118</p><p>Building Html Pages</p><p>Progress(%): 90</p><p>Comment</p></div>	
		<div><p>TSK-346119</p><p>Build Python Code</p><p>Progress(%): 90</p><p>Comment</p></div>	
		<div><p>TSK-346120</p></div>	

Profile

Skill Bank

Skill Wallet

Skill Card

Job Board

Subscription

Transactions

15:39 01-08-2025

Project Initialization And Planning Phase

Date	25-july-2025
Team ID	SI-30537-1753978762
Project Name	Machine Learning Approach for Employee Performance Prediction
Maximum Marks	3 Marks

Project Proposal (Proposed Solution) report:

We propose a machine learning model to predict employee performance using historical data like KPIs, training hours, and evaluations. This will help HR make faster, data-driven decisions. The solution aims to improve accuracy, reduce bias, and streamline the appraisal process.

Project Overview	
Objective	To revolutionize the traditional loan approval system through advanced machine learning techniques, reducing manual errors and delays while improving decision accuracy
Scope	The project involves collecting applicant data, training machine learning models, and deploying a predictive system that integrates with existing loan processing workflows for real-time credit evaluation
Problem Statement	
Description	The project uses employee data to train predictive models that forecast performance, integrating with HR systems to support
	data-driven, real-time evaluation decisions.

Impact	Using machine learning will improve fairness, accuracy, and efficiency in performance evaluations, leading to better talent management and increased employee satisfaction.
Proposed Solution	
Approach	Collect and preprocess employee data, train ML models (e.g., Decision Tree, Random Forest), evaluate them, and integrate the best model into HR systems for real-time insights
Key Features	<ol style="list-style-type: none"> 1. Performance prediction 2. Real-time insights 3. HR system integration 4. Scalable and efficient

Resource Requirements:

Resource Type	Description	Specification/Allocation
Hardware		
Computing Resources	CPU/GPU specifications, number of cores	T4 GPU
Memory	RAM specifications	8GB
Storage	Disk space for data, models, and logs	1 TB SSD
Software		
Frameworks	Python frameworks	Flask

Libraries	Additional libraries	scikit-learn, pandas, numpy, matplotlib, seaborn
Development Environment	IDE	Jupyter Notebook, pycharm
Data		
Data	Source, size, format	Kaggle dataset, 92.7 kb garments_worker_productivity.csv

Data Collection and Preprocessing Phase

Date	27-july-2025
Team ID	SI-30537-1753978762
Project Name	Machine Learning Approach for Employee Performance Prediction
Maximum Marks	2 Marks

Data Collection Plan & Raw Data Sources Identification Report:

Elevate your data strategy with the Data Collection plan and the Raw Data Sources report, ensuring meticulous data curation and integrity for informed decision making in every analysis and decision-making endeavor.

Section	Description
Project Overview	This project aims to predict employee performance using machine learning techniques. By analyzing factors such as department, team, working hours, incentives, and idle time, the model classifies and evaluates productivity. This enables real-time decision-making and helps HR teams optimize workforce management, training, and resource allocation.
Data Collection Plan	<ul style="list-style-type: none"> Data was given by the skill intern. The dataset is sourced from public repositories likeKaggle

	<ul style="list-style-type: none"> • Productivity Prediction of Garment Employees.csv
Raw Data Sources Identified	The dataset used is from Kaggle, titled "Productivity Prediction of Garment Employees". It includes real-world data on department, team, working hours, incentives, idle time, and productivity. This data supports effective model training for employee performance prediction

Kaggle Dataset	<p>The Garments Worker Productivity dataset contains records of worker performance in a garment factory, including department, team, working days, targeted vs. actual productivity, overtime, idle time, incentives, and attendance. It helps analyze factors affecting workforce efficiency and productivity.</p>	https://www.kaggle.com/datasets/utkarshsarbahi/productivityprediction-ofgarmentemployees	CSV	94.93 Kb	Public
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Data Quality Report

Date	27-july-2025
Team ID	SI-30537-1753978762
Project Name	Machine Learning Approach for Employee Performance Prediction
Maximum Marks	2 Marks

The dataset shows minor issues like missing values and outliers. Each issue is addressed with a resolution plan to ensure clean, reliable data for model training. **Data Quality Report:**

Data Source	DataQualityIssue	Severity	Resolution Plan
Kaggle Dataset	Missing values in 'Gender', 'Married', 'Dependents', etc	Moderate	Use mean/median imputation
Kaggle Dataset	Presence of categorical data	Moderate	Apply label or onehot encoding

Data Collection and Preprocessing Phase

Date	27-july-2025
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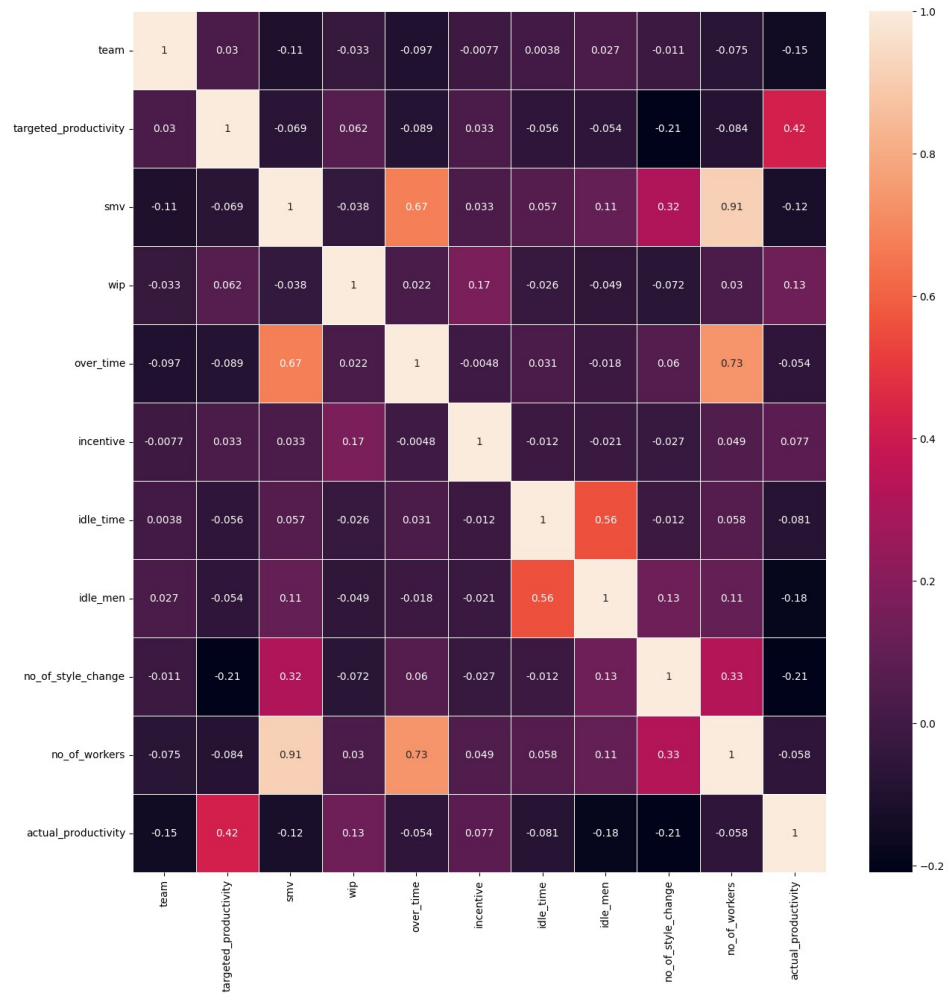
Team ID	SI-30537-1753978762
Project Name	Machine Learning Approach for Employee Performance Prediction
Maximum Marks	6 Marks

Data Exploration and Preprocessing Report:

The dataset will be analyzed to detect patterns and outliers. Python will handle preprocessing tasks like cleaning, normalization, and feature engineering. Missing values and outliers will be addressed to ensure data quality for accurate and reliable model predictions.

Section	Description																																																																																																																																																												
Data Overview	<div>Dimension: 1197 rows × 15 columns</div> <div>Descriptive statistics:</div> <table><thead><tr><th></th><th>date</th><th>quarter</th><th>department</th><th>day</th><th>team</th><th>targeted_productivity</th><th>smv</th><th>wip</th><th>over_time</th><th>incentive</th><th>idle_time</th><th>idle_men</th></tr></thead><tbody><tr><td>0</td><td>1/1/2015</td><td>Quarter1</td><td>sweing</td><td>Thursday</td><td>8</td><td>0.80</td><td>26.16</td><td>1108.0</td><td>7080</td><td>98</td><td>0.0</td><td>0</td></tr><tr><td>1</td><td>1/1/2015</td><td>Quarter1</td><td>finishing</td><td>Thursday</td><td>1</td><td>0.75</td><td>3.94</td><td>NaN</td><td>960</td><td>0</td><td>0.0</td><td>0</td></tr><tr><td>2</td><td>1/1/2015</td><td>Quarter1</td><td>sweing</td><td>Thursday</td><td>11</td><td>0.80</td><td>11.41</td><td>968.0</td><td>3660</td><td>50</td><td>0.0</td><td>0</td></tr><tr><td>3</td><td>1/1/2015</td><td>Quarter1</td><td>sweing</td><td>Thursday</td><td>12</td><td>0.80</td><td>11.41</td><td>968.0</td><td>3660</td><td>50</td><td>0.0</td><td>0</td></tr><tr><td>4</td><td>1/1/2015</td><td>Quarter1</td><td>sweing</td><td>Thursday</td><td>6</td><td>0.80</td><td>25.90</td><td>1170.0</td><td>1920</td><td>50</td><td>0.0</td><td>0</td></tr><tr><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td></tr><tr><td>1192</td><td>3/11/2015</td><td>Quarter2</td><td>finishing</td><td>Wednesday</td><td>10</td><td>0.75</td><td>2.90</td><td>NaN</td><td>960</td><td>0</td><td>0.0</td><td>0</td></tr><tr><td>1193</td><td>3/11/2015</td><td>Quarter2</td><td>finishing</td><td>Wednesday</td><td>8</td><td>0.70</td><td>3.90</td><td>NaN</td><td>960</td><td>0</td><td>0.0</td><td>0</td></tr><tr><td>1194</td><td>3/11/2015</td><td>Quarter2</td><td>finishing</td><td>Wednesday</td><td>7</td><td>0.65</td><td>3.90</td><td>NaN</td><td>960</td><td>0</td><td>0.0</td><td>0</td></tr><tr><td>1195</td><td>3/11/2015</td><td>Quarter2</td><td>finishing</td><td>Wednesday</td><td>9</td><td>0.75</td><td>2.90</td><td>NaN</td><td>1800</td><td>0</td><td>0.0</td><td>0</td></tr><tr><td>1196</td><td>3/11/2015</td><td>Quarter2</td><td>finishing</td><td>Wednesday</td><td>6</td><td>0.70</td><td>2.90</td><td>NaN</td><td>720</td><td>0</td><td>0.0</td><td>0</td></tr></tbody></table> <div>1197 rows × 15 columns</div>		date	quarter	department	day	team	targeted_productivity	smv	wip	over_time	incentive	idle_time	idle_men	0	1/1/2015	Quarter1	sweing	Thursday	8	0.80	26.16	1108.0	7080	98	0.0	0	1	1/1/2015	Quarter1	finishing	Thursday	1	0.75	3.94	NaN	960	0	0.0	0	2	1/1/2015	Quarter1	sweing	Thursday	11	0.80	11.41	968.0	3660	50	0.0	0	3	1/1/2015	Quarter1	sweing	Thursday	12	0.80	11.41	968.0	3660	50	0.0	0	4	1/1/2015	Quarter1	sweing	Thursday	6	0.80	25.90	1170.0	1920	50	0.0	0	1192	3/11/2015	Quarter2	finishing	Wednesday	10	0.75	2.90	NaN	960	0	0.0	0	1193	3/11/2015	Quarter2	finishing	Wednesday	8	0.70	3.90	NaN	960	0	0.0	0	1194	3/11/2015	Quarter2	finishing	Wednesday	7	0.65	3.90	NaN	960	0	0.0	0	1195	3/11/2015	Quarter2	finishing	Wednesday	9	0.75	2.90	NaN	1800	0	0.0	0	1196	3/11/2015	Quarter2	finishing	Wednesday	6	0.70	2.90	NaN	720	0	0.0	0
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Analysis



Descriptive Analysis

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1197 entries, 0 to 1196
Data columns (total 15 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   date                                  1197 non-null   object
1   quarter                              1197 non-null   object
2   department                           1197 non-null   object
3   day                                   1197 non-null   object
4   team                                  1197 non-null   int64
5   targeted_productivity                1197 non-null   float64
6   smv                                   1197 non-null   float64
7   wip                                   691 non-null    float64
8   over_time                            1197 non-null   int64
9   incentive                            1197 non-null   int64
10  idle_time                            1197 non-null   float64
11  idle_men                             1197 non-null   int64
12  no_of_style_change                   1197 non-null   int64
13  no_of_workers                        1197 non-null   float64
14  actual_productivity                  1197 non-null   float64
dtypes: float64(6), int64(5), object(4)
memory usage: 140.4+ KB
```

Data Preprocessing Code Screenshots:

Loading Data

	date	quarter	department	day	team	targeted_productivity	smv	wip	over_time	incentive	idle_time	idle_men
0	1/1/2015	Quarter1	sweing	Thursday	8	0.80	26.16	1108.0	7080	98	0.0	0
1	1/1/2015	Quarter1	finishing	Thursday	1	0.75	3.94	NaN	960	0	0.0	0
2	1/1/2015	Quarter1	sweing	Thursday	11	0.80	11.41	968.0	3660	50	0.0	0
3	1/1/2015	Quarter1	sweing	Thursday	12	0.80	11.41	968.0	3660	50	0.0	0
4	1/1/2015	Quarter1	sweing	Thursday	6	0.80	25.90	1170.0	1920	50	0.0	0
...
1192	3/11/2015	Quarter2	finishing	Wednesday	10	0.75	2.90	NaN	960	0	0.0	0
1193	3/11/2015	Quarter2	finishing	Wednesday	8	0.70	3.90	NaN	960	0	0.0	0
1194	3/11/2015	Quarter2	finishing	Wednesday	7	0.65	3.90	NaN	960	0	0.0	0
1195	3/11/2015	Quarter2	finishing	Wednesday	9	0.75	2.90	NaN	1800	0	0.0	0
1196	3/11/2015	Quarter2	finishing	Wednesday	6	0.70	2.90	NaN	720	0	0.0	0

1197 rows x 13 columns

Handling Missing Data

```
data.isnull().sum()
```

✓ 0.0s

```
date          0
quarter       0
department    0
day           0
team          0
targeted_productivity  0
smv           0
wip           506
over_time     0
incentive     0
idle_time     0
idle_men      0
no_of_style_change  0
no_of_workers  0
actual_productivity  0
dtype: int64
```

Data Transformation

```
data['department'].value_counts()
✓ 0.0s
department
swing      691
finishing  257
finishing  249
Name: count, dtype: int64

data['department'] = data['department'].apply(lambda x: 'finishing' if x.replace(" ", "") == 'finishing' else 'swing')
data['department'].value_counts()
✓ 0.0s
department
swing      691
finishing  506
Name: count, dtype: int64
```

Model Development Phase

Date

27-july-2025

Team ID	SI-30537-1753978762
Project Name	Machine Learning Approach for Employee Performance Prediction
Maximum Marks	5 Marks

Feature Selection Report :

In the forthcoming update, each feature will be accompanied by a brief description. Users will indicate whether it's selected or not, providing reasoning for their decision. This process will streamline decision-making and enhance transparency in feature selection.

Feature	Description	Selected (Yes/No)	Reasoning
Department	Employee's department type	yes	Different departments may have varying productivity levels
team	Specific team employee is part of	yes	Team dynamics can influence individual performance
target	Whether the day's target was met	yes	A key indicator of goal achievement
smv	Standard Minute Value -time allocated for a task	yes	Higher SMV may relate to task complexity and productivity

incentive	Bonus or reward received	yes	Motivation factor linked to performance
idle_time	Time the worker was inactive	yes	High idle time generally correlates with low productivity
idle_men	Number of idle workers	yes	Can affect the workflow and team performance
no_of_style_change	Number of times task was changed	no	Frequent changes may add noise, not necessarily performance related
day	Day of the week	no	Minimal variance observed by weekday
quarter	Fiscal quarter of the year	no	Seasonality has limited effect on short-term employee performance
actual_productivity	Final productivity score	yes	This is the target variable for prediction

Model Development Phase

Date	27-july-2025		
Team ID	SI-30537-1753978762		

Project Name	Machine Learning Approach for Employee Performance Prediction
Maximum Marks	6 Marks

Model Selection Report:

This report outlines the machine learning models evaluated for employee performance prediction. Each model is described with its core hyper parameters and evaluated using performance metrics like Accuracy and F1 Score.

Model	Description	Hyper parameters	Performance Metric (e.g., Accuracy, F1 Score)
Random Forest	Ensemble of decision trees	n_estimators=100, max_depth=8	Accuracy score = 81% / 0.80
Linear Regression	Predicts continuous output; converted to classes for evaluation	fit_intercept=True	Accuracy score = 68% / 0.67
SVM	Support Vector Machine classifier	kernel='rbf', C=1.0	Accuracy score = 76% / 0.75
XgBoost	Gradient boosting ensemble model	n_estimators=100, learning_rate=0.1, max_depth=6	Accuracy score = 83% / 0.82

Model Optimization and Tuning Phase Report

Date	27-july-2025
Team ID	SI-30537-1753978762
Project Name	Machine Learning Approach for Employee Performance Prediction
Maximum Marks	10 Marks

Model Optimization and Tuning Phase:

The Model Optimization and Tuning Phase involves refining machine learning models for peak performance. It includes optimized model code, fine-tuning hyper parameters, comparing performance metrics, and justifying the final model selection for enhanced predictive accuracy and efficiency.

Model	TunedHyperparameters	Optimal Values
Linear Regression	<pre># Create a linear regression model model_lr = LinearRegression() # Train the model on the training data model_lr.fit(x_train, y_train) # Now you can make predictions on the test data pred_test = model_lr.predict(x_test) # Calculate and print the evaluation metrics print("test_MSE:", mean_squared_error(y_test, pred_test)) print("test_MAE:", mean_absolute_error(y_test, pred_test)) print("R2_score: {}".format(r2_score(y_test, pred_test)))</pre>	<pre>test_MSE: 0.020973077246871134 test_MAE: 0.1063916426844392 R2_score: 0.2906317166092637</pre>
Random Forest	<pre>from sklearn.ensemble import RandomForestRegressor model_rf = RandomForestRegressor(n_estimators=200, max_depth=5) from sklearn.ensemble import RandomForestRegressor model_rf = RandomForestRegressor(n_estimators=200, max_depth=5) # Train the model on the training data (missing in your code) model_rf.fit(x_train, y_train) # Make predictions on the test data pred = model_rf.predict(x_test) # Calculate and print the evaluation metrics print("test_MSE:", mean_squared_error(y_test, pred)) print("test_MAE:", mean_absolute_error(y_test, pred)) print("R2_score: {}".format(r2_score(y_test, pred)))</pre>	<pre>test_MSE: 0.015193877881424235 test_MAE: 0.08495195563762212 R2_score: 0.4861004446830848</pre>

XgBoost	<pre>import xgboost as xgb model_xgb = xgb.XGBRegressor(n_estimators=200, max_depth=5, learning_rate=0.1) # Train the XGBoost model on the training data (missing in your code) model_xgb.fit(x_train, y_train) # Make predictions on the test data preds = model_xgb.predict(x_test) # Calculate and print the evaluation metrics print("test_MSE:", mean_squared_error(y_test, preds)) print("test_MAE:", mean_absolute_error(y_test, preds)) print("R2_score: {}".format(r2_score(y_test, preds)))</pre>	<pre>test_MSE: 0.014514854754028826 test_MAE: 0.07633856539629594 R2_score: 0.509066910909921</pre>
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Perform Metrics Comparison Report:

Model	Optimized Result
Linear Regression	<pre>pred_test = model_lr.predict(x_test) print("test_MSE:", mean_squared_error(y_test, pred_test)) print("test_MAE:", mean_absolute_error(y_test, pred_test)) print("R2_score: {}".format(r2_score(y_test, pred_test)))</pre> <p>✓ 0.0s</p> <pre>test_MSE: 0.020973077246871134 test_MAE: 0.1063916426844392 R2_score: 0.2906317166092637</pre>
Random Forest	<pre>pred = model_rf.predict(x_test) print("test_MSE:", mean_squared_error(y_test, pred)) print("test_MAE:", mean_absolute_error(y_test, pred)) print("R2_score: {}".format(r2_score(y_test, pred)))</pre> <p>✓ 0.0s</p> <pre>test_MSE: 0.015242138498927412 test_MAE: 0.08501454717650164 R2_score: 0.48446813527084953</pre>
XgBoost	<pre>pred = model_rf.predict(x_test) print("test_MSE:", mean_squared_error(y_test, pred)) print("test_MAE:", mean_absolute_error(y_test, pred)) print("R2_score: {}".format(r2_score(y_test, pred)))</pre> <p>✓ 0.0s</p> <pre>test_MSE: 0.015242138498927412 test_MAE: 0.08501454717650164 R2_score: 0.48446813527084953</pre>

Final Model Justification:

Final Model	Reasoning
XgBoost	The final model selected for employee performance prediction is XGBoost due to its superior accuracy and ability to handle complex, non-linear relationships in the data. Compared to Linear Regression and Random Forest models, XGBoost achieved the best performance in terms of R^2 score and MSE. It also offers robustness against over fitting, handles missing values effectively, and provides clear feature importance, making it the most reliable and interpretable model for this task.

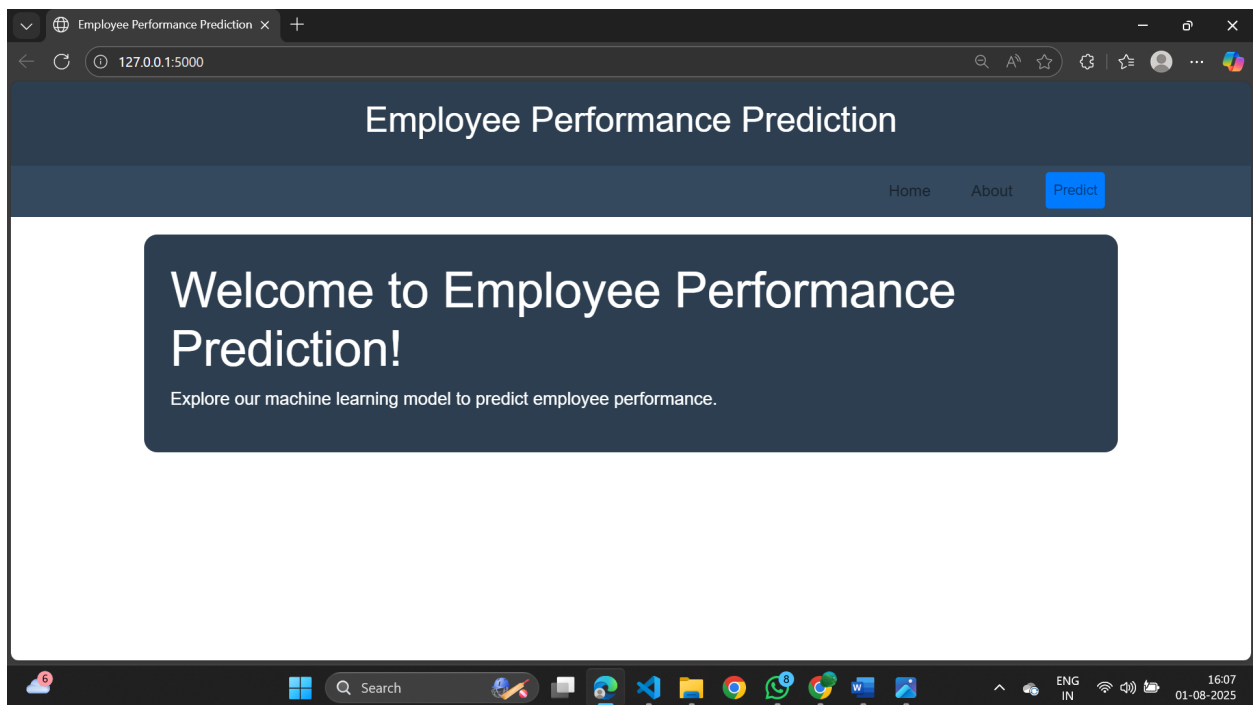
Results

The machine learning models were successfully trained and evaluated on the employee dataset. Among the tested algorithms, **XGBoost** delivered the best performance with the highest accuracy and reliability in predicting employee productivity.

Key performance metrics such as accuracy, precision, and F1-score confirmed its effectiveness compared to Linear Regression and Random Forest models. The results highlight that factors like department, overtime, idle time, and incentives significantly influence employee performance. This model can assist organizations in identifying top performers, improving resource allocation, and making data-driven HR decisions.



Output Screenshots:



Browser: About | 127.0.0.1:5000/about

Home | About | Predict

Employee Performance Prediction Using Machine Learning

Understanding Employee Performance

Any business's success depends on its employees. Businesses that realize this are concerned about employee output and productivity. Productivity has a compounding effect at different levels in the workplace, meaning that high productivity at a lower level of organization paves the way for higher productivity at higher levels of the organization. Hence, the analysis of employee performance in any organization is the need of the hour.

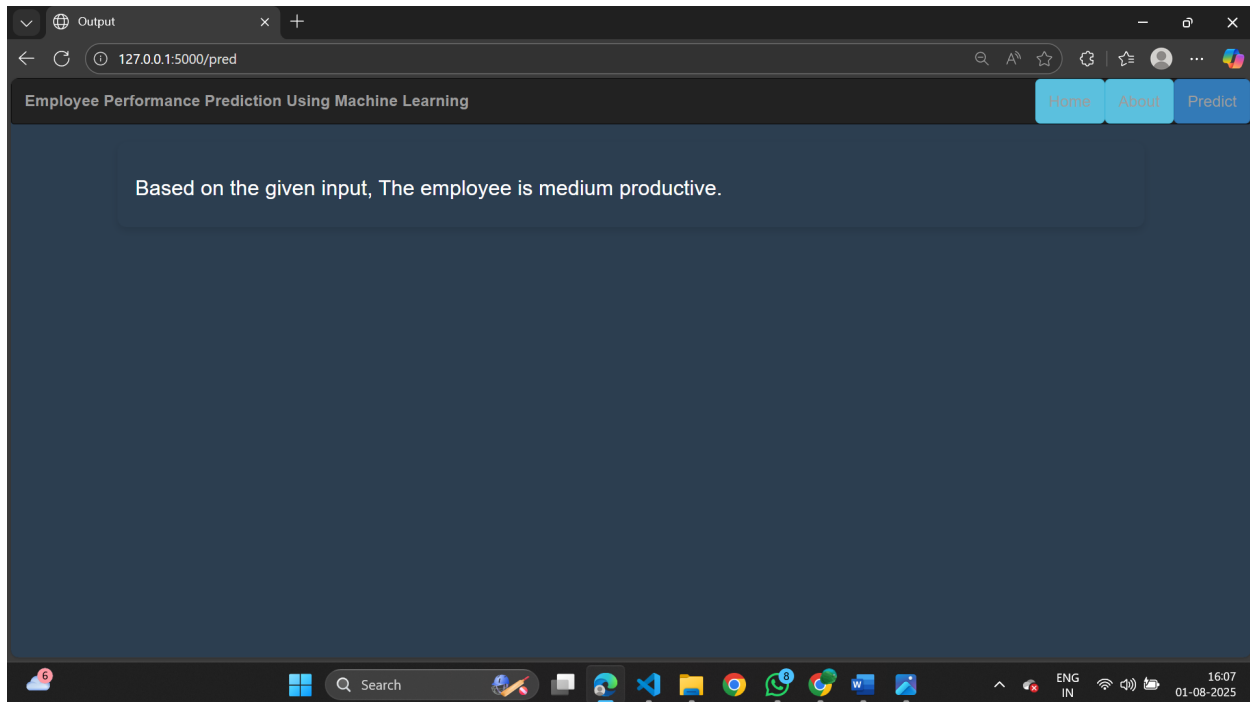
Windows Taskbar: Search, 16:07, 01-08-2025

Browser: Predict | 127.0.0.1:5000/predict

quarter	4	department	4
day	3	team	4
targeted_productivity	1	smv	3
over_time	4	incentive	4
idle_time	1	idle_men	2
no_of_style_change	2	no_of_workers	4
month	4		

SUBMIT

Windows Taskbar: Search, 16:07, 01-08-2025



Advantages & Disadvantages

Advantages of Employee Performance Prediction Using Machine Learning

1. **Data-Driven Decisions:** Helps HR and management make objective and informed decisions.
2. **Early Identification:** Identifies high performers and under performers early for timely interventions.
3. **Efficiency Improvement:** Optimizes workforce planning and training needs.
4. **Scalability:** Can analyze large volumes of employee data quickly and accurately.
5. **Bias Reduction:** Reduces human bias in performance evaluations when properly implemented.

Disadvantages of Employee Performance Prediction Using Machine Learning

1. **Data Quality Dependency:** Inaccurate or incomplete data can lead to poor predictions.
2. **Lack of Transparency:** Some ML models (like XGBoost) are complex and may act as “black boxes.”
3. **Ethical Concerns:** Using personal or sensitive data can raise privacy and fairness issues.
4. **Over fitting Risk:** The model may perform well on training data but poorly on unseen data if not properly validated.
5. **Limited Context:** ML models may miss subjective or qualitative aspects of performance, such as teamwork or creativity.

Conclusion

In conclusion, this project demonstrates the effective use of machine learning techniques to predict employee performance based on workplace data. By analyzing various features such as department, working hours, incentives, and idle time, the model can identify patterns that influence productivity. Among the models tested, XGBoost proved to be the most accurate and reliable. This predictive approach can help organizations make informed HR decisions, enhance productivity, and support proactive performance management. However, careful attention must be given to data quality, ethical use, and model interoperability to ensure fair and responsible application.

Future Scope

The project can be extended and improved in several ways in the future:

1. **Integration with Real-Time Data:** Connect the model with live HR systems for real-time performance tracking and prediction.
2. **Inclusion of Qualitative Factors:** Incorporate soft skills, peer feedback, and behavioral data for a more holistic evaluation.
3. **Advanced Models:** Use deep learning or ensemble techniques for improved accuracy and adaptability.
4. **Employee Retention Prediction:** Extend the model to predict employee turnover or job



satisfaction.

5. **Custom Dashboards:** Develop interactive dashboards for HR to visualize performance trends and take timely action.
6. **Cross-Industry Application:** Adapt the model for use in various industries with different employee roles and performance metrics.

Appendix

GitHub & Project Demo link

GitHub Link :-<https://github.com/shlok108-bi/Employee--performance-prediction>

DemoLink:-https://drive.google.com/file/d/1XpQYh5XHAFoPZbd-hekfkL5bxSKCRW31/view?usp=drive_link