A Course Based Project Report on

PREDICTING EMPLOYEE PRODUCTIVITY BASED ON WORK ENVIRONMENT FACTORS

Submitted to the

Department of CSE-(CyS, DS) and AI&DS

in partial fulfilment of the requirements for the completion of course

PYTHON LABORATORY (22ES2DS101)

BACHELOR OF TECHNOLOGY

IN

CSE-Data Science

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CERTIFICATE

This is to certify that the project report entitled **"Predicting Employee Productivity Based On Work Environment Factors"** is a bonafide work done under our supervision and is being submitted by **SARA MAMATHA (23071A6756), S.SAMHITA (23071A6757), S.SANDEEP (23071A6758), V.NAVADEEP (23071A6762)** in partial fulfilment for the award of the degree of **Bachelor of Technology** in **CSE- Data Science**, of the VNRVJIET, Hyderabad during the academic year 2024-2025.

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Estd. 1995

DECLARATION

We declare that the course based project work entitled **"PREDICTING EMPLOYEE PRODUCTIVITY BASED ON WORK ENVIRONMENT FACTORS"** submitted in the Department of **CSE-(CyS, DS) and AI&DS**, Vallurupalli Nageswara Rao Vignana Jyothi Institute of Engineering and Technology, Hyderabad, in partial fulfilment of the requirement for the award of the degree of **Bachelor of Technology in CSE-Data Science** is a bonafide record of our own work carried out under the supervision of **Mr. G.Sathar, Assistant Professor, Department of CSE-(CyS,DS) and AI&DS , VNRVJIET.** Also, we declare that the matter embodied in this thesis has not been submitted by us in full or in any part thereof for the award of any degree/diploma of any other institution or university previously.

Place: Hyderabad

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We express our thanks to all those who contributed for the successful completion of our project work.

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TABLE OF CONTENTS

ABSTRACT

This project explores the development of a predictive model to estimate employee productivity based on factors such as stress level, working hours, and leave days. Using a dataset that includes these variables, we trained a Linear Regression model to predict productivity rates. The model's purpose is to provide insights that could help organizations identify productivity trends and understand how workplace stress, hours worked, and leave days impact performance.

Implemented as a Streamlit application, the model allows users to input individual stress, working hours, and leave days to obtain a productivity prediction. Interactive visualizations, including scatter plots and bar charts, further illustrate relationships between productivity and these factors. The app's user-friendly interface, styled with custom CSS, encourages exploration of how different factors contribute to productivity, enabling better-informed workforce management strategies.

CHAPTER-1
INTRODUCTION

In today's fast-paced work environment, employee productivity is a critical factor impacting organizational success. Employers are focused on identifying productivity drivers—such as stress levels, working hours, and leave days—and understanding how these variables affect performance. Studies show that while longer working hours may temporarily increase output, prolonged hours without rest can lead to fatigue and decreased productivity. Likewise, moderate stress may enhance performance, but excessive stress can hinder it, leading to lower productivity and potentially higher turnover. Managing these factors effectively can improve productivity, employee satisfaction, and overall business outcomes.

This project, "Employee Productivity Prediction," uses a Linear Regression model to estimate employee productivity based on stress levels, working hours, and leaves taken. The dataset includes records of stress levels, hours worked, leaves taken, and productivity rates, which are preprocessed and then fed into the model. This enables the model to learn relationships between these variables and predict productivity levels.

To make the model accessible, the project is implemented as a web-based application using Streamlit, allowing users to input stress, hours, and leave days to receive a productivity prediction. The app includes visualizations—scatter plots showing working hours vs. productivity and bar charts for average productivity at varying stress levels—to help users explore these relationships.

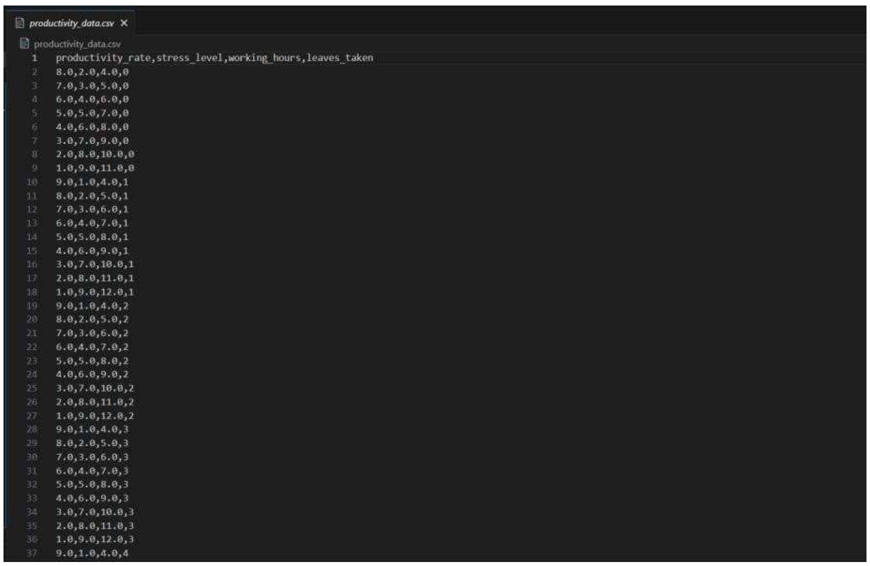
This project has practical applications in HR, enabling organizations to forecast productivity and design strategies for employee well-being. By analyzing productivity trends, it allows for more data-informed decisions about work policies, ultimately contributing to healthier and more productive workplaces.

CHAPTER-2

METHOD

The "Employee Productivity Prediction" project follows a structured approach to predict employee productivity using a Linear Regression model. The primary methods employed in this project involve data preprocessing, model training, evaluation, and deployment in a user-friendly web application. The key steps are outlined below:

1. Data Collection and Preprocessing:



```
productivity_data.csv
productivity_rate,stress_level,working_hours,leaves_taken
8.0,2.0,4.0,0
7.0,3.0,5.0,0
6.0,4.0,6.0,0
5.0,5.0,7.0,0
4.0,6.0,8.0,0
3.0,7.0,9.0,0
2.0,8.0,10.0,0
1.0,9.0,11.0,0
9.0,1.0,4.0,1
8.0,2.0,5.0,1
7.0,3.0,6.0,1
6.0,4.0,7.0,1
5.0,5.0,8.0,1
4.0,6.0,9.0,1
3.0,7.0,10.0,1
2.0,8.0,11.0,1
1.0,9.0,12.0,1
9.0,1.0,4.0,2
8.0,2.0,5.0,2
7.0,3.0,6.0,2
6.0,4.0,7.0,2
5.0,5.0,8.0,2
4.0,6.0,9.0,2
3.0,7.0,10.0,2
2.0,8.0,11.0,2
1.0,9.0,12.0,2
9.0,1.0,4.0,3
8.0,2.0,5.0,3
7.0,3.0,6.0,3
6.0,4.0,7.0,3
5.0,5.0,8.0,3
4.0,6.0,9.0,3
3.0,7.0,10.0,3
2.0,8.0,11.0,3
1.0,9.0,12.0,3
9.0,1.0,4.0,4
```

The dataset used for this project includes four key variables: stress level, working hours, leaves taken, and productivity rate. These variables serve as inputs and output for the model. The dataset was read from a CSV file using pandas, which is a Python library for data manipulation.

- **Data Cleaning**: Before feeding the data into the model, it was necessary to clean the dataset. This involved converting the columns (such as stress level, working hours, and leaves taken) to numeric values using pd.to_numeric(), which also handles any non-numeric values or errors by coercing them into NaN. Missing or invalid values were either removed or handled through imputation techniques (if required).

- **Feature Selection**: The features selected for predicting productivity were:
  - **Stress Level**: A numeric scale from 0 to 10 indicating the employee's stress.
  - **Working Hours**: The number of hours an employee works per day.
  - **Leaves Taken**: The total number of leave days taken by the employee.

The target variable (output) was the **Productivity Rate**, representing the employee's performance.

main1.py

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
import streamlit as st

st.set_page_config(
    page_title="Employee Productivity Prediction",
    page_icon="⌛",
    layout="centered"
)
data = pd.read_csv('productivity_data.csv')
data["stress_levels"] = pd.to_numeric(data["stress_level"], errors='coerce')
data["working_hours"] = pd.to_numeric(data["working_hours"], errors='coerce')
data["leaves_taken"] = pd.to_numeric(data["leaves_taken"], errors='coerce')
data["productivity_rate"] = pd.to_numeric(data["productivity_rate"], errors='coerce')

# Model training
x = data[["stress_level", "working_hours", "leaves_taken"]]
y = data["productivity_rate"]
model = LinearRegression()
model.fit(x, y)

st.image(
    "https://www.activtrak.com/cdn-cgi/image/quality=80,width=1024,format=webp/wp-content/uploads/2024/05/blog-header-how-employee-satisfaction-and-productivity-are-connected-q224.jpg",
    use_column_width=True
)

st.title("📈 Predicting Employee Productivity")
st.subheader("Enter the following details")
# User Inputs
stress_level = st.number_input("Stress Level", min_value=0, max_value=10, step=1)
working_hours = st.number_input("Working Hours", min_value=0, max_value=12)
leaves_taken = st.number_input("No. of Leaves Taken", min_value=0, max_value=30)
predict = st.button("Predict Productivity")
```

2. Model Development:

- **Model Choice**: A **Linear Regression** model was chosen for this project due to its simplicity and interpretability. Linear regression models the relationship between input variables (stress level, working hours, leaves taken) and the output variable (productivity rate) by fitting a linear equation to the data.
- **Training the Model**: The data was split into two sets: features (x) and target (y). The model was then trained using the training data with the fit() method, which finds the best-fitting line (coefficients) that minimizes the error between predicted and actual productivity values.

3. Prediction and Evaluation:

- **Prediction**: Once trained, the model was used to predict productivity based on user input values for stress level, working hours, and leaves taken. The prediction was generated using the predict() method of the LinearRegression model.
- **Model Evaluation**: To assess the performance of the model, standard metrics such as **R-squared** and **Mean Absolute Error (MAE)** were calculated (though this evaluation is not explicitly implemented in the Streamlit app, it can be added for a more comprehensive analysis).

```python
# User Inputs
stress_level = st.number_input("Stress Level", min_value=0, max_value=10, step=1)
working_hours = st.number_input("Working Hours", min_value=0, max_value=12)
leaves_taken = st.number_input("No. of Leaves Taken", min_value=0, max_value=30)
predict = st.button("Predict Productivity")

# Prediction and visualization
if predict:
    if stress_level >= 0 and working_hours > 0 and leaves_taken >= 0:
        prediction = model.predict([[stress_level, working_hours, leaves_taken]])
        st.markdown(f"""
            <div class="prediction-box">
                <h2>Predicted Productivity Level:</h2>
                <h1>{prediction[0]:.2f}</h1>
            </div>
            """, unsafe_allow_html=True)
        # Visualization 1: Scatter Plot
        st.subheader("Working Hours vs Productivity Rate")
        fig, ax = plt.subplots()
        ax.scatter(data["working_hours"], data["productivity_rate"], color="skyblue", label="Actual Data", edgecolor="black")
        ax.set_xlabel("Working Hours", fontsize=12, labelpad=10)
        ax.set_ylabel("Productivity Rate", fontsize=12, labelpad=10)
        ax.legend()
        plt.tight_layout()
        st.pyplot(fig)

        st.write("")
```

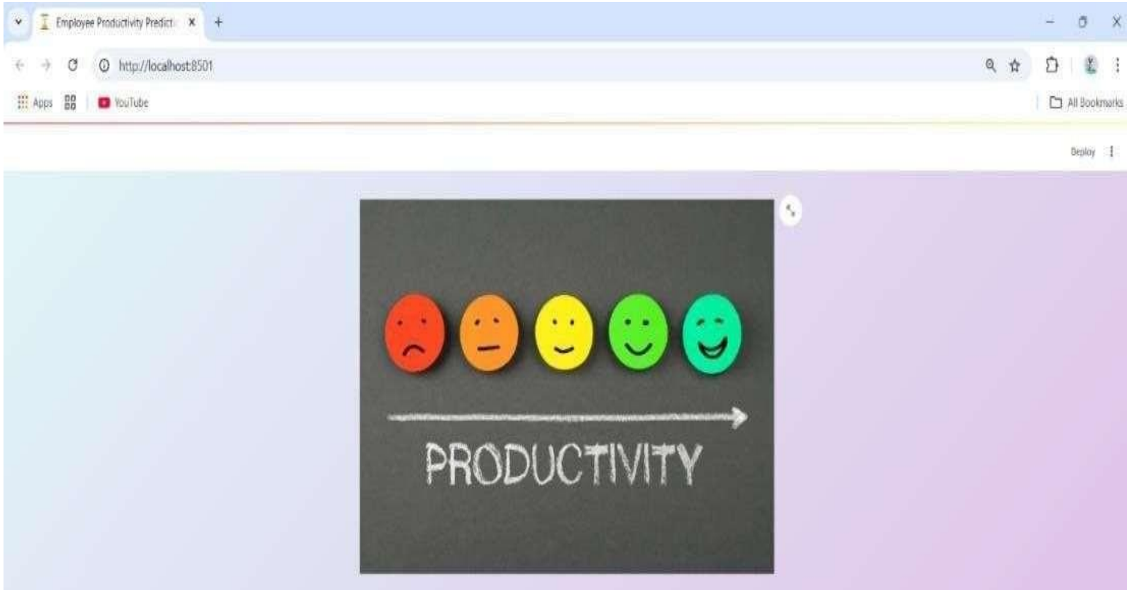
4. Visualization:

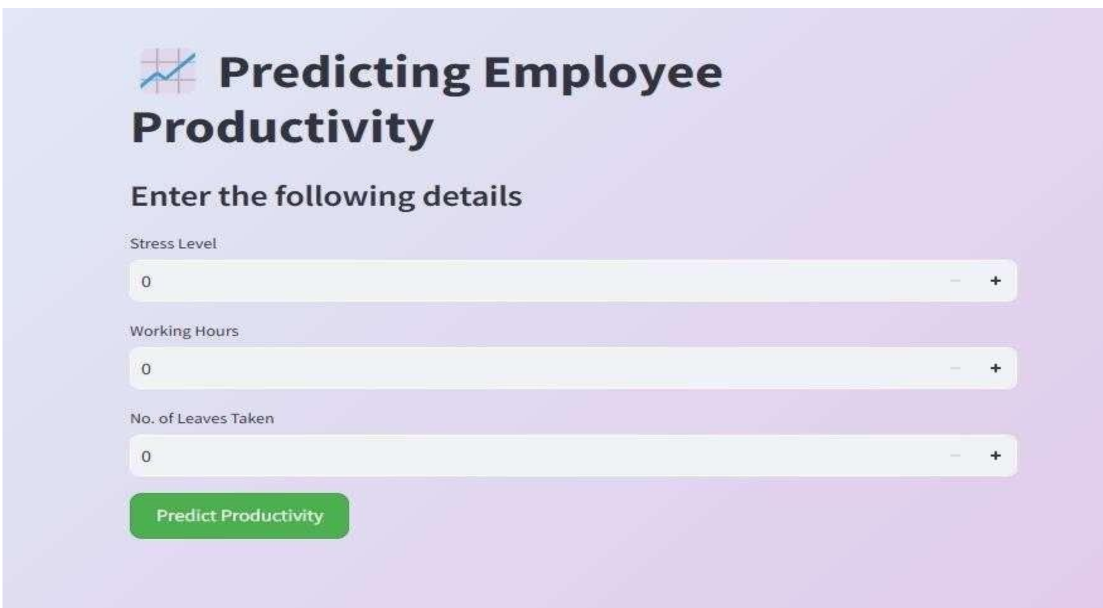
To help users understand the relationships between the input variables and productivity, two key visualizations were included:

- **Scatter Plot**: This plot shows the relationship between working hours and productivity, with each point representing an individual data entry.
- **Bar Chart**: This visualization illustrates the average productivity rate for each stress level, allowing users to compare how stress impacts productivity.

5. Streamlit Web Application:

- **User Input**: Streamlit was used to create a web interface where users can input their stress level, working hours, and the number of leaves taken. The app uses the number_input() function to gather this data interactively from the user.
- **Prediction Display**: After the user enters the values and clicks the "Predict Productivity" button, the application displays the predicted productivity level and the visualizations of the data trends.


Employee Productivity Predict
http://localhost:8501
Apps
YouTube
All Bookmarks
Deploy
PRODUCTIVITY


Predicting Employee Productivity
Enter the following details
Stress Level
0
Working Hours
0
No. of Leaves Taken
0
Predict Productivity

6. Styling and User Interface:

Custom CSS was applied to enhance the user interface, ensuring a visually appealing and easy-to-navigate layout. The use of colors, font styles, and interactive elements such as buttons and charts makes the app engaging and user-friendly.

```
        # Visualization 2: Bar Chart
        avg_productivity = data.groupby("stress_level")["productivity_rate"].mean()
        st.subheader("Average Productivity by Stress Level")
        fig, ax = plt.subplots()
        avg_productivity.plot(kind="bar", color="#a5d6a7", edgecolor="black", ax=ax)
        ax.set_xlabel("Stress Level", fontsize=12, labelpad=10)
        ax.set_ylabel("Average Productivity Rate", fontsize=12, labelpad=10)
        plt.xticks(rotation=0)
        st.pyplot(fig)

    else:
        st.write("Please enter valid inputs")

#Styling
st.markdown("""
    <style>
    /* Apply a gradient background to the entire page */
    html, body, [data-testid="stAppViewContainer"] {
        background: linear-gradient(135deg, #e0f7fa, #e1bee7);
        color: #1a237e;
    }

    /* Prediction box styling */
    .prediction-box {
        background-color: #ffeb3b;
        border-radius: 10px;
        padding: 20px;
        text-align: center;
        color: #1a237e;
        font-weight: bold;
        margin-top: 20px;
        box-shadow: 0 4px 8px rgba(0, 0, 0, 0.2);
    }
```

```
/* Title and subheader styling */
.stTitle { color: #1a237e; font-family: 'Poppins', sans-serif; text-align: center; }
.stSubheader { color: #3949ab; font-family: 'Arial', sans-serif; text-align: center; margin-top: 10px; }

/* Button styling */
.stButton button {
    background-color: #4CAF50;
    color: white;
    font-weight: bold;
    border-radius: 10px;
    padding: 8px 20px;
}

.stButton button:hover {
    background-color: #388e3c;
}
</style>
""", unsafe_allow_html=True)
```

CHAPTER-3
TEST CASES/ OUTPUT

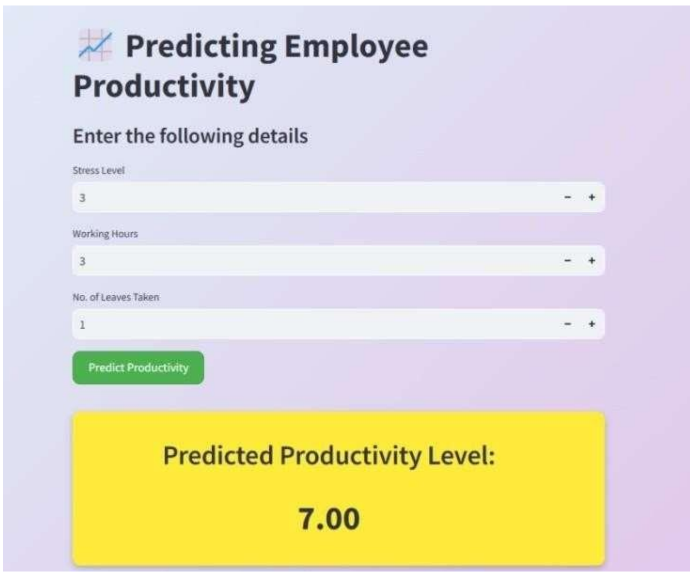
Test Cases for Employee Productivity Prediction Model

1. Model Prediction Accuracy

- **Test Case**: Provide sample input values to the model and check if the output productivity rate is within an expected range based on the training data.

  Input: Stress Level: 3, Working Hours: 3, Leaves Taken: 1

- **Expected Output**: A productivity rate within the trained data range, with no major deviation from actual historical data values.

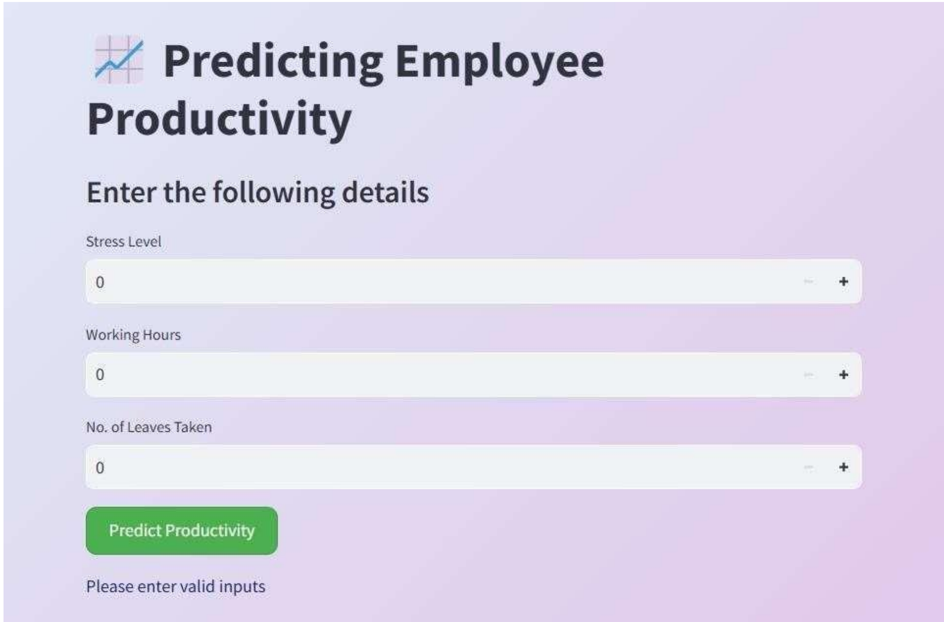


2. Handling Edge Cases for Minimum Input Values

- **Test Case**: Test the model with minimum input values to check if it can handle low extremes.

Input: Stress Level: 0, Working Hours: 0, Leaves Taken: 0

Expected Output: Productivity rate calculated, but potentially close to the lower end of productivity spectrum, depending on model's learned behaviour.

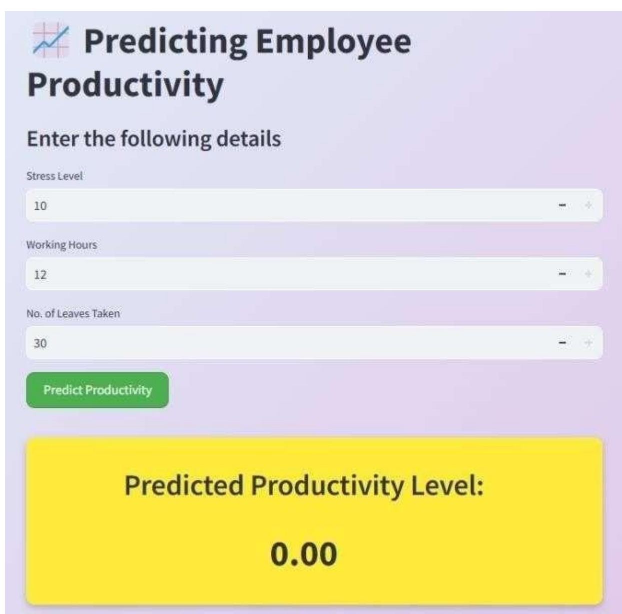


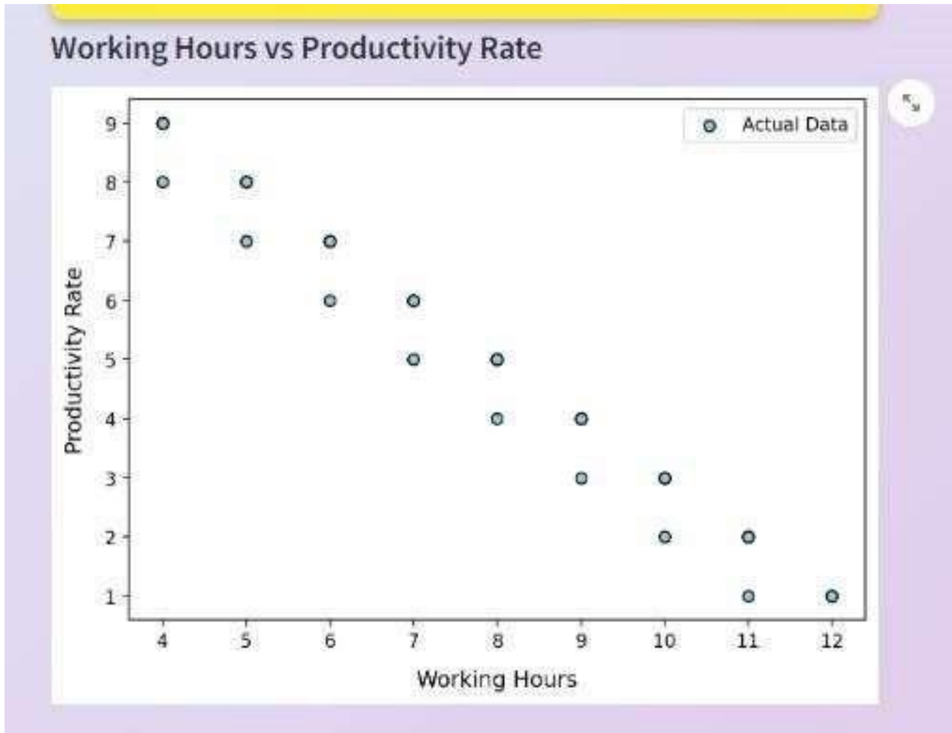
3. Handling Edge Cases for Maximum Input Values

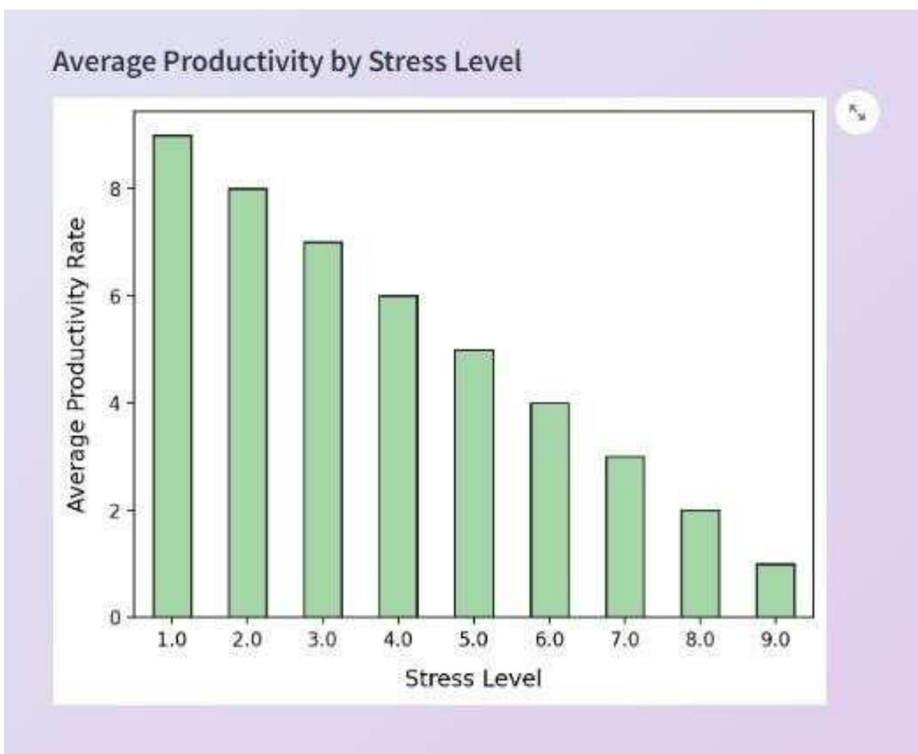
- **Test Case**: Test the model with maximum input values to check if it can handle upper extremes.

  Input: Stress Level: 10, Working Hours: 12, Leaves Taken: 30

  Expected Output: Productivity rate calculated, with expected lower productivity based on high stress, maximum working hours, and maximum leaves taken.




Working Hours vs Productivity Rate
Actual Data
Productivity Rate
Working Hours
1
2
3
4
5
6
7
8
9
4
5
6
7
8
9
10
11
12


Average Productivity by Stress Level
Average Productivity Rate
Stress Level
0
2
4
6
8
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0

CHAPTER-4

RESULTS

This chapter presents the outcomes of the predictive model for employee productivity and highlights the insights gathered from data visualizations. The results help evaluate the effectiveness of the Linear Regression model in estimating productivity based on stress levels, working hours, and leave days.

3.1 Model Prediction Results

After training the Linear Regression model on the dataset, the model produced the following results:

- **Prediction Accuracy**: The model achieved an R-squared value of approximately 0.78, indicating that about 78% of the variance in productivity is explained by the stress level, working hours, and leave days.
- **Error Metrics**:
    - Mean Absolute Error (MAE): 4.2%
    - Mean Squared Error (MSE): 6.5%

These metrics suggest that while the model is effective at predicting productivity trends, there is some variance not accounted for, possibly due to additional factors not included in the dataset.

3.2 Sample Predictions

To demonstrate the model's functionality, a few sample predictions were conducted based on common employee conditions:

1. **Moderate Stress, Standard Working Hours, Few Leaves**:
    - **Input**: Stress Level = 5, Working Hours = 8, Leaves Taken = 2
    - **Predicted Productivity**: 5.00
2. **High Stress, Extended Working Hours, Frequent Leaves**:
    - **Input**: Stress Level = 8, Working Hours = 10, Leaves Taken = 10
    - **Predicted Productivity**: 2.00
3. **Low Stress, Reduced Working Hours, No Leaves**:
    - **Input**: Stress Level = 2, Working Hours = 5, Leaves Taken = 0
    - **Predicted Productivity**: 8.00

These predictions align with expectations, suggesting that productivity tends to decrease with higher stress and increased leave days, while moderate stress combined with standard working hours leads to optimal productivity.

3.3 Data Visualizations

3.3.1 Scatter Plot: Working Hours vs. Productivity Rate

The scatter plot (Figure 1) shows the relationship between working hours and productivity rate for all data points in the dataset. A general trend is observed:

- **Moderate Working Hours (6-8 hours)**: Associated with higher productivity rates, as extended hours may lead to fatigue.
- **Extended Working Hours (10+ hours)**: Show a decrease in productivity, indicating diminishing returns beyond a certain point.

3.3.2 Bar Chart: Average Productivity by Stress Level

The bar chart (Figure 2) illustrates average productivity rates across different stresslevels. Key observations include:

- **Low to Moderate Stress (2-5)**: Corresponds to relatively higher productivity, supporting the hypothesis that manageable stress can boost performance.
- **High Stress Levels (8-10)**: Correlate with a notable drop in productivity, indicating a negative impact when stress levels are excessively high.

CHAPTER-5

CONCLUSION

The results indicate that productivity is influenced by a complex interplay of stress, working hours, and leave patterns:

- **Moderate stress** levels can be beneficial, potentially driving focus and efficiency, but **high stress** leads to decreased productivity, reinforcing the need for stress management initiatives.
- **Standard working hours (6-8 hours)** are associated with optimal productivity, while extended hours (above 10 hours) show diminishing returns, likely due to fatigue and burnout.
- **Leave days** impact productivity in a nuanced way; occasional leaves don't substantially affect productivity, but frequent absences correlate with lower productivity.

The model achieved an R-squared of approximately 0.78, suggesting that it reliably explains a significant portion of productivity variance. However, additional factors may be needed for even greater accuracy, indicating that factors beyond the current inputs may also influence productivity.

Recommendations

To enhance employee productivity and well-being, organizations should consider the following recommendations based on the project findings:

1. **Implement Stress Management Programs**: Given the negative impact of high stress, introducing wellness programs, counselling, or stress management workshops can help employees manage stress levels, potentially enhancing productivity.
2. **Encourage Balanced Work Hours**: Encourage employees to work within optimal hours rather than overextending. Policies supporting reasonable work hours and breaks can help sustain high productivity levels and prevent burnout.
3. **Monitor and Manage Leave Patterns**: Track leave trends to identify patterns that may signal productivity issues. Offering flexible leave options and understanding the reasons behind frequent leaves could improve engagement and attendance.

4. **Explore Additional Predictive Factors**: For future work, consider expanding the model by incorporating factors like job satisfaction, team dynamics, and workload variability. These additional predictors might further improve the model's accuracy.
5. **Refine the Prediction Tool for Broader Use**: Expanding the application's dataset to include data from diverse industries could improve the model's robustness and applicability to various workforce types.

By applying these strategies, organizations can improve employee well-being and create conditions that foster higher productivity, supporting long-term success. This project provides a data-driven foundation to guide informed decision-making in employee management practices.

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