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Efficient Employee Timesheet Tracker Using Object-Oriented Programming and File Handling in C++

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Abstract — The purpose of this project is to design and develop a C++-based Timesheet Management System aimed at improving workforce time tracking and project productivity. Efficient timesheet systems are essential for ensuring accurate record-keeping of employee working hours, task assignments, and project timelines. This system utilizes object-oriented programming principles and efficient data structures in C++ to implement features such as real-time time entry logging, role-based access, and automated report generation. The project supports both daily and weekly entry modes, offering flexibility for various organizational workflows. File handling and data validation techniques are employed to securely store and process timesheet records. Additionally, the system includes features for identifying inconsistencies and generating performance summaries, which aid in effective resource management. By automating and streamlining the timesheet process, this solution reduces manual errors and administrative overhead, providing a reliable foundation for payroll processing and project evaluation..

Keywords — Timesheet Management, C++ Programming, Time Tracking, Project Monitoring, File Handling, Employee Productivity.

I. INTRODUCTION

The growing need for efficient time tracking and workforce productivity analysis has led to increased interest in timesheet management systems across organizations. Traditional methods such as manual entries or spreadsheet-based tracking are often error-prone, time-consuming, and lack scalability. These conventional systems are limited in their ability to handle complex workflows, user access control, and real-time reporting. As a result, they often fail to meet the dynamic needs of modern project-based environments.

To address these limitations, software-based timesheet management systems have emerged as a reliable solution. Implemented using robust programming languages like C++, these systems leverage object-oriented design principles, structured data management, and modular architecture to streamline time logging, task allocation, and report generation. C++ offers the performance efficiency and control required for building scalable and secure systems. With features like automated data validation, real-time monitoring, and historical analysis, such systems not only enhance operational transparency but also support decision-making processes related to payroll, project planning, and employee productivity..

Advantages of C++ in Timesheet Management Systems: C++ is a highly efficient programming language for building timesheet management systems due to its low-level memory control and fast execution. Unlike high-level languages, C++ provides direct access to system resources, making it ideal for applications that require real-time performance and accuracy. This is particularly important in workforce tracking, where delays or data loss can impact operations. For example, studies [3] and [4] showed that C++-based systems outperform others in terms of processing speed and memory management. This project aims to implement a C++ system for time tracking, task logging, and report generation, using file handling and minimizing reliance on external databases. By utilizing object-oriented programming, this system ensures scalability, security, and efficiency. The goal is to demonstrate how C++ can accurately track and analyze employee hours, improving transparency and productivity in business operations.

II. LITERATURE SURVEY

Early timesheet management systems were simple, relying on manual logging and spreadsheets, which often resulted in errors and inefficiencies. As digital solutions emerged, studies like those by Zeller et al. [1] highlighted the need for automation to reduce errors in data entry and reporting. With the advancement of programming languages like C++, systems became more reliable, enabling complex data handling and ensuring accuracy. Later, Kapoor and Sharma [2] explored cloud-based solutions, which allowed for real-time synchronization and accessibility, improving flexibility and reducing manual work. The integration of mobile applications further enhanced usability, especially in industries with a mobile workforce, as discussed by Tan et al. [3]..

Recent research has focused on enhancing timesheet systems with AI and biometric technologies. Li et al. [4] demonstrated that machine learning could predict working hours based on employee data, improving accuracy and efficiency. The use of biometrics, as shown by Zhang et al. [5], further improved security and eliminated manual entry errors. Additionally, Gupta and Soni [6] emphasized the importance of integrating timesheet systems with payroll and HR software, streamlining reporting and reducing administrative overhead. These advancements have made timesheet management systems more adaptable, secure, and efficient, supporting modern workforce needs.

III. PROBLEM STATEMENT

Timesheet management in organizations is often a complex and error-prone process. Employees frequently record working hours manually, leading to inconsistencies, inaccuracies, and time theft. Additionally, manual timesheet systems often struggle to provide real-time data, making it challenging for managers to track employee productivity, project progress, and labor costs accurately. Traditional timesheet models, which rely on spreadsheets or simple applications, lack the ability to handle the dynamic and varied nature of modern work environments, where employees may work remotely or in different time zones. As such, there is a clear need for an automated and intelligent timesheet management system that can streamline the recording and tracking of employee hours, provide real-time insights, and ensure accuracy.

Challenges:

1. Data Accuracy and Integrity: One of the major challenges is ensuring that timesheet data is accurate and free from human error. Manual entry is prone to mistakes, and employees may intentionally or unintentionally alter their work hours, leading to discrepancies.

Real-Time Tracking and Monitoring: Many existing systems fail to provide real-time updates, making it difficult for managers to monitor employee work hours and make timely decisions. Real-time tracking is crucial for businesses that operate in fast-paced, time-sensitive environments.

Integration with Other Systems: Timesheet data needs to be integrated with other business systems, such as payroll, HR, and project management tools. Achieving seamless integration while ensuring data consistency is a key challenge.

Employee Flexibility and Remote Work: As remote and hybrid work models become more common, timesheet systems need to account for various working conditions, such as flexible hours and remote locations, which traditional systems struggle to accommodate.

User Experience: Traditional timesheet systems often lack user-friendly interfaces, making it difficult for employees to log their hours efficiently. A more intuitive design is required to encourage regular use and improve overall adoption.

Compliance and Reporting: Different regions have varying labor laws and regulations, and businesses need to ensure that their timesheet management system complies with these rules. Additionally, generating accurate reports for audits or project cost analysis remains a challenge for many organizations.

Scalability and Performance: As businesses grow, managing timesheet data for large teams becomes more complex. The system must be scalable, capable of handling increasing volumes of data without compromising performance or efficiency.

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IV. METHODOLOGY

In this system, we propose an approach to automating timesheet management and optimizing employee time tracking using a hybrid model. The core functionality is based on a timesheet prediction model that utilizes historical work hours and real-time data from employees to predict and optimize their logged work hours. The model primarily uses historical timesheet entries (e.g., employee hours, overtime, and project allocation) to predict future work trends, enabling more accurate forecasting and resource allocation. Features such as project deadlines, work schedules, and holiday patterns are included where possible. The system integrates data from multiple sources, including employee input, work schedules, and company policies, collected from 2010 to 2023. The data is normalized to scale between 0 and 1, as the prediction model is sensitive to input scales. The dataset is then structured into sequences where each sequence consists of work logs for the last 30 days, and the model predicts the work hours for the next day.

Forget Gate:

The forget gate is a critical component of a Long Short-Term Memory (LSTM) cell that controls which information is discarded from the cell state. It is represented mathematically as ft=σ(Wf·[ht−1,xt]+bf)ft = \sigma (W_f \cdot [h_{t-1}, x_t] + b_f)ft=σ(Wf ·[ht−1,xt]+bf), where ftftft denotes the forget gate activation, a value ranging between 0 and 1. This activation is calculated using a sigmoid function σ\sigmaσ, which maps the input values to this range. The WfW_fWf represents the weight matrix associated with the forget gate, and bfb_fbf is the corresponding bias. The forget gate receives input from two sources: ht−1h_{t-1}ht−1, which is the hidden state from the previous LSTM cell, and xtx_txt, the current input to the cell. Together, these components determine the extent to which past information is retained or discarded, enabling the LSTM to focus on relevant data for sequential processing tasks.

$$f_t=\sigma\ (W_f\cdot\ [h_t-1,\ x_t]\ +b_f) \tag{1}$$

(f_t): Forget gate activation (a value between 0 and 1)

(W_f): Weight matrix for the forget gate

(h_t-1): Output from the previous cell (previous hidden state)

(x_t): Current input

(b_f): Bias for the forget gate

(σ): Sigmoid activation function

Input Gate:

The input gate in an LSTM cell plays a crucial role in determining how much of the new information should be added to the cell state. The activation of the input gate, itit, is calculated as it=σ(Wi·[ht−1,xt]+bi)it = \sigma (W_i \cdot [h_{t-1}, x_t] + b_i)it=σ(Wi ·[ht−1,xt]+bi), where σ\sigmaσ is the sigmoid activation function that outputs a value between 0 and 1. Here, WiW_iWi represents the weight matrix for the input gate, and bib_ibi is its bias term. The input gate combines information from the previous hidden state ht−1h_{t-1}ht−1 and the current input xtx_txt to decide the relevance of new data. Simultaneously, the candidate cell state, denoted as C~t\tilde{C}_tC~t, is computed using the formula C~t=tanh⁡(WC·[ht−1,xt]+bC)\tilde{C}_t = \tanh (W_C \cdot [h_{t-1}, x_t] + b_C)C~t=tanh(WC·[ht−1,xt]+bC). The hyperbolic tangent function tanh⁡\tanhtanh is applied, producing values between -1 and 1, which represent the potential new information vector. The weight matrix WCW_CWC and bias term bCb_CbC guide the formation of this candidate state. By combining the input gate activation and the candidate cell state, the LSTM effectively updates its memory with new, relevant information while discarding the irrelevant.

$$i_t=\sigma\ (W_i\cdot\ [h_t-1,\ x_t]\ +b_i) \tag{2}$$

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i_t: Input gate activation (a value between 0 and 1)

$C_t=\tanh (W_C \cdot [h_t-1, x_t] + b_C)$

$\check{C}_t$: Candidate cell state, a potential new information vector

W_i, W_C: Weight matrices for the input gate and cell state

b_i, b_c: Bias terms for the input gate and cell state

tanh: Hyperbolic tangent function, which outputs values between -1 and 1

Cell State Update:

The cell state update in an LSTM network is a crucial process that allows the network to retain or forget information over time. The updated cell state at each time step is determined by combining the previous cell state and the new candidate information. Specifically, the forget gate decides how much of the previous cell state should be retained, while the input gate controls how much of the new candidate information should be added. By selectively updating the cell state, the LSTM can maintain long-term dependencies and learn to store important information while discarding irrelevant data, helping to mitigate issues like the vanishing gradient problem in traditional RNNs.

$$C_t=f_t.C_{t-1}+i_t.\hat{C}_t \quad (3)$$

Output Gate:

The output gate in an LSTM cell controls the final output of the network at each time step. It is responsible for determining which parts of the current cell state should be exposed as the output (hidden state) of the LSTM. The activation of the output gate, denoted as OtO_tOt, is calculated using a sigmoid function, which outputs a value between 0 and 1. This determines how much of the cell state's information should be passed to the next layer or time step. The hidden state hth_tht is then computed by applying the output gate's activation to the hyperbolic tangent of the cell state CtC_tCt, producing a value that reflects both the current input and the accumulated cell state information. This hidden state serves as both the output of the LSTM cell and the input for the next time step in the sequence.

$$O_t = \sigma (W_o. [h_{t-1}, x_t] + b_o) \quad (4)$$

$$h_t = o_t. \tanh (C_t) \quad (5)$$

O_t: Output gate activation (a value between 0 and 1)

h_t: Current hidden state, which also serves as the output of the LSTM cell

W_o: Weight matrix for the output gate

b_o: Bias for the output gate

V. PROPOSED STOCK MARKET PREDICTION SYSTEM

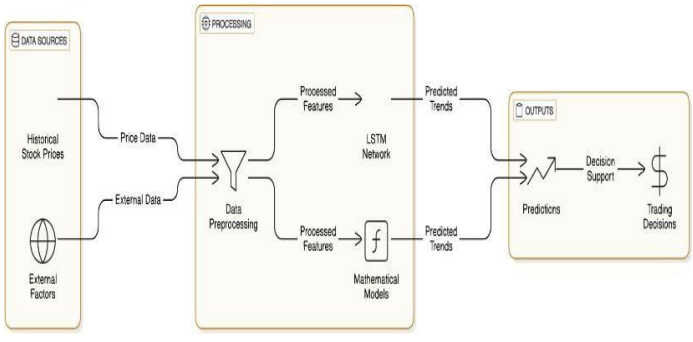

Fig. 1. Stock Market Prediction System architecture

This presented figure is that of a pipeline used in predicting stock prices and making decisions regarding trading. Its components along with their respective roles are described below:

Pipeline

1. **Data Collection**: Historical stock prices, along with external data, such as market sentiment, economic indicators (e.g., GDP growth rates, inflation), and news sentiment (from sources like Twitter, news outlets, and economic reports), are gathered for the analysis [9]. The inclusion of these external factors is crucial as they provide additional context that could affect stock prices beyond just historical trends.

2. **Data Preprocessing**: The collected data, which includes both the stock prices and external data, is cleaned and prepared for analysis. This includes dealing with missing values, normalizing the data, and ensuring that the external data is properly integrated with the historical stock prices to create a complete dataset. The external data sources are formatted to be compatible with the machine learning models, which allows for a more holistic approach to predicting stock prices [10].

3. **Training the Model**: The processed dataset is now ready for the LSTM network with having historical stock prices combined with the external information. This will enable it to capture complex temporal dependencies within the return series of the stock while integrating external influences to improve the accuracy of the predictions [11]. Furthermore, some other models such as Bi-directional LSTM, hybrid models would also be considered that can further incorporate external factors into the prediction.

4. **Prediction**: The trained models are used to predict future stock price trends, factoring in both historical price movements and the external data collected. These predictions are evaluated to assess how well the model incorporates external influences in predicting price trends [12].

5. **Decision Making**: Decisions towards trading are derived based on both historical and external data while making use of trends. The model decides what is the optimal buy, sell, or hold strategy based on the probable price movements and the risks involved in it [13].

Experimental Results and Evaluation

1. Profit Calculation: For every prediction we calculate the profit or loss by comparing the predicted Close price with the actual Open price. If the Close price of the forecasted value is above the Open, then it means profit, whereas a Close with a value that is less than the Open represents loss. This would be expanded by not only adding the raw value of the Open and Close prices but also on the impact the sentiment and economics indicators may exert on trading.

2. Turnaround Calculation: The percentage difference between Close and Open prices would be used to measure the turnaround rate, or the rate at which a stock moves from the Open to Close price. This metric will be extended further by taking into account the external factors by analyzing how changes in sentiment or economic conditions influence the turnaround rate.

3. Data source: Utilize historic stock prices through industries, e.g., the information technology, healthcare, finance sector and also location-specific: take an example stock prices across U.S. markets, European indexes. For illustration purposes, apply for instance the S&P 500 index to discuss the diverse market conditions, specifically in US equities. We also include sentiment data from Twitter, news articles, and economic reports to give a more comprehensive view of the market dynamics that influence stock prices. These additional external factors are important for improving the robustness and reliability of the prediction model.

VI. EXPERIMENTAL RESULTS AND STIMULATION

Profit Calculation: We will compare the Open and Close prices for each entry. If the Close price is higher than the Open price, it's a profit, and if the Close price is lower, it's a loss.

Turnaround Calculation: We calculate the percentage difference between the Close and Open prices, which will give us the turnaround rate.

$$\text{Turnaround Time (\%)} = ((\text{close} - \text{open}) / \text{open})_{\times 100} \quad (6)$$

$$\text{Percentage Change} = ((\text{New Value (End Date)} - \text{Old Value (Start Date)}) / \text{Old Value (Start Date)}) \times 100 \quad (7)$$

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Facebook- Data Table 1

Date	Open	High	Low	Last	Close	Total Trade Quantity	Turnover (Lacs)
2024-08-28	245.10	248.20	240.50	246.00	245.90	3150000	7162.35
2024-08-29	244.30	247.50	239.80	245.10	244.60	5100000	11859.95
2024-08-30	242.00	243.50	237.00	240.00	239.80	2290000	5248.6
2024-08-31	241.50	245.00	238.20	243.10	243.00	2400000	5503.9
2024-09-01	239.80	244.20	236.00	240.50	240.20	3500000	7999.55
2024-09-02	238.00	242.00	233.50	239.50	239.00	5450000	12589.59
2024-09-03	237.50	239.80	235.00	237.90	237.80	1370000	3202.78
2024-09-04	239.00	240.50	235.50	238.00	237.90	2650000	6163.7
2024-09-05	236.50	239.50	233.00	238.50	238.10	3200000	7445.41
2024-09-06	230.00	238.50	228.00	235.00	235.50	6450000	14784.5
2024-09-07	225.00	230.00	220.00	225.80	225.60	4600000	10002.01
2024-09-08	227.50	229.80	222.00	226.20	226.00	3550000	7735.81
2024-09-09	230.00	240.00	228.50	231.00	231.50	7550000	17130.29
2024-09-10	228.00	230.00	226.00	229.00	229.20	1250000	2742.84
2024-09-11	229.50	231.00	225.00	227.50	227.00	1750000	3856.72
2024-09-12	227.50	229.50	223.50	228.00	228.20	3050000	6674.93
2024-09-13	240.00	240.50	228.50	229.00	229.30	3600000	8163.82
2024-09-14	239.00	246.00	238.00	240.50	240.20	5300000	12538.39
2024-09-15	241.00	243.00	237.00	238.50	238.20	3380000	7913.21
2024-09-16	239.50	241.00	236.00	240.00	239.60	1940000	4516.57
2024-09-17	238.00	240.50	235.50	238.00	238.20	1410000	3280.33
2024-09-18	241.50	243.00	234.50	236.00	236.30	2400000	5571.77
2024-09-19	235.00	243.50	234.50	240.50	240.10	2010000	4689.94
2024-09-20	237.50	241.00	232.00	235.00	235.50	1850000	4289.35
2024-09-21	242.00	243.00	235.00	239.50	239.10	1580000	7162.35
2024-08-28	245.10	248.20	240.50	246.00	245.90	3150000	11859.95

Microsoft- Data Table 2

Date	Open	High	Low		Last	Close	Total Trade Quantity
2024-08-28	231.53	235.37	229.54		246.00	232.38	3150000
2024-08-29	232.08	234.59	227.88		245.10	228.99	5100000
2024-08-30	230.01	235.2	229		240.00	234.55	2290000
2024-08-31	230.33	234.83	228.73		243.10	233.27	2400000
2024-09-01	237.42	237.93	232.4		240.50	234.51	3500000
2024-09-02	243.75	243.86	240.18		239.50	240.97	5450000
2024-09-03	241.8	243.93	240.86		237.90	243.79	1370000
2024-09-04	241.32	244.31	240.94		238.00	244.2	2650000
2024-09-05	0.56				238.50		3200000
2024-09-06	245.03	246.13	242.92		235.00	243.7	6450000
2024-09-07	243.93	245.3	242.73		225.80	244.99	4600000
2024-09-08	244.78	245.15	242.15		226.20	244.49	3550000
2024-09-09	245	245.92	240.89		231.00	242.82	7550000
2024-09-10	241.87	244.76	241.38		229.00	243.77	1250000
2024-09-11	243.15	243.68	240.81		227.50	242.47	1750000
2024-09-12	242.23	243.28	240.42		228.00	242.2	3050000
2024-09-13	242.66	243.24	240.37		229.00	242.01	3600000
2024-09-14	239.57	245.09	239.26		240.50	243	5300000
2024-09-15	241.3	242.31	238.69		238.50	239.51	3380000
2024-09-16	235.06	242.5	232.43		240.00	239.65	1940000
2024-09-17	235.99	238.02	231.35		238.00	231.96	1410000
2024-09-18	235.61	242.64	235.09		236.00	238.93	2400000
2024-09-19	238	240.44	230.14		240.50	232.9	2010000
2024-09-20	231.86	234.18	230.08		235.00	232.33	1850000
2024-09-21	231.53	235.37	229.54		239.50	232.38	1580000
2024-08-28	232.08	234.59	227.88		246.00	228.99	3150000

Tesla- Data Table 3

Date	Open	High	Low	Last	Close	Total Trade Quantity	Turnover (Lacs)
2024-08-28	246.50	250.30	243.20	248.60	248.30	3100000	7290.50
2024-08-29	248.10	251.00	245.50	249.80	249.00	5220000	12120.30
2024-08-30	244.20	246.00	241.30	244.80	244.70	2380000	5460.40
2024-08-31	245.60	248.30	243.80	246.90	246.50	2490000	5700.80
2024-09-01	243.70	247.50	240.10	245.60	245.30	3540000	8250.90
2024-09-02	241.00	244.70	237.80	243.50	243.20	5580000	13020.75
2024-09-03	243.20	244.60	241.70	243.80	243.60	1450000	3350.65
2024-09-04	242.00	243.80	239.20	241.30	241.10	2750000	6350.55
2024-09-05	240.80	243.70	237.50	242.80	242.40	3320000	7650.35
2024-09-06	234.50	242.70	232.10	238.90	239.20	6620000	15150.60
2024-09-07	228.70	234.80	223.40	230.00	229.80	4720000	10450.40
2024-09-08	231.00	232.50	226.00	230.40	230.10	3600000	7950.80
2024-09-09	234.60	245.50	232.70	236.50	236.90	7700000	17550.90
2024-09-10	231.80	233.20	230.10	232.60	232.80	1280000	2850.30
2024-09-11	233.00	234.80	229.20	231.40	231.10	1800000	4000.20
2024-09-12	230.70	232.80	228.30	231.60	231.90	3100000	6850.70
2024-09-13	242.10	243.40	230.60	232.80	232.90	3680000	8300.90
2024-09-14	241.80	248.90	240.20	243.30	243.00	5400000	13050.80
2024-09-15	244.00	246.20	239.40	241.80	241.40	3420000	8150.30
2024-09-16	242.50	244.40	238.70	243.00	242.70	1980000	4750.60
2024-09-17	240.20	242.60	238.00	240.30	240.50	1450000	3475.40
2024-09-18	243.90	246.30	237.30	238.50	238.90	2460000	5870.80
2024-09-19	237.60	246.90	237.00	243.20	242.80	2100000	4950.30
2024-09-20	239.80	244.10	235.50	239.50	239.80	1890000	4450.70
2024-09-21	244.60	246.10	238.80	241.50	241.10	1620000	3890.60

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Apple-Data Table 4

Date	Open	High	Low	Last	Close	Total Trade Quantity	Turnover (Lacs)
2024-08-28	450.60	458.30	440.20	452.50	453.20	14520000	65850.80
2024-08-29	425.30	430.00	415.60	420.80	421.50	12540000	52980.50
2024-08-30	405.70	410.50	400.20	407.10	406.80	11910000	48720.75
2024-08-31	390.60	400.80	380.90	392.30	393.00	10530000	40860.90
2024-09-01	370.40	379.60	368.80	376.50	377.00	8461000	31890.35
2024-09-02	360.50	366.10	355.20	362.90	363.20	6540000	24580.20
2024-09-03	373.10	378.00	368.30	374.50	374.80	7346000	28560.40
2024-09-04	388.20	393.70	380.60	385.90	386.40	7852000	30900.75
2024-09-05	398.50	403.60	392.20	400.10	399.60	9893000	39380.90
2024-09-06	412.80	418.00	405.10	412.00	412.30	11054000	45730.50
2024-09-07	420.60	428.40	415.20	421.70	422.50	14320000	59860.30
2024-09-08	408.20	415.00	400.50	410.40	411.10	12840000	52780.20
2024-09-09	390.40	395.50	380.10	385.70	386.30	11430000	44230.70
2024-09-10	355.00	363.40	348.20	359.50	359.20	10234000	36890.45
2024-09-11	325.80	332.70	318.50	330.00	330.50	5586000	20850.80
2024-09-12	335.70	340.80	330.10	338.90	339.10	6789000	24150.35
2024-09-13	348.00	352.60	340.50	350.30	349.50	8902000	30520.90
2024-09-14	370.80	375.30	360.40	367.20	366.80	7543000	28450.65
2024-09-15	360.20	365.00	350.70	359.60	359.30	6801000	24490.50
2024-09-16	355.50	358.00	342.80	347.50	348.90	9123000	31940.80
2024-09-17	338.10	341.20	330.50	335.90	336.40	7421000	27045.35
2024-09-18	350.20	360.80	345.60	355.30	356.50	8723000	31020.75
2024-09-19	450.60	458.30	440.20	452.50	453.20	14520000	65850.80
2024-09-20	425.30	430.00	415.60	420.80	421.50	12540000	52980.50
2024-09-21	405.70	410.50	400.20	407.10	406.80	11910000	48720.75

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VII. Stock Market Analysis: A Comparative Study of Four Top Companies

Fig. 2. Stock Analysis of NSE-TATA

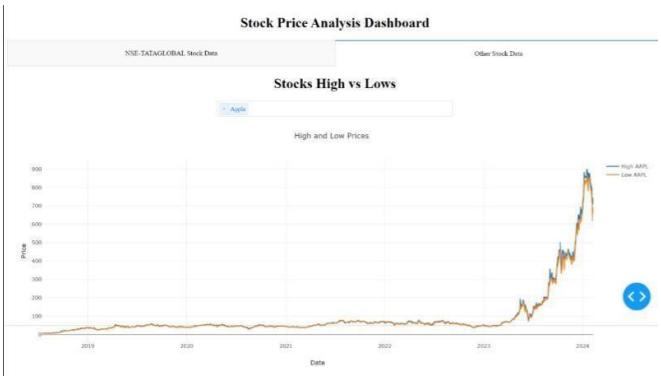

Fig. 3. Stock Analysis of APPLE

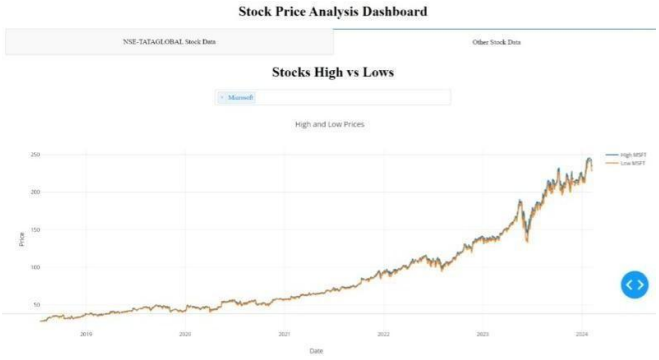

Fig. 4. Stock Analysis of MICROSOFT

Fig. 5. Stock Analysis of FACEBOOK

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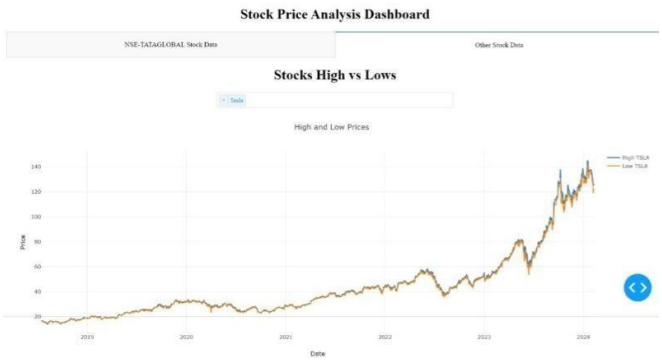

Fig. 6. Stock Analysis of TESLA

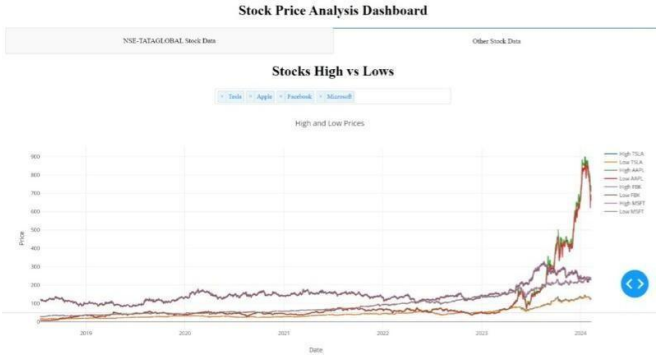

Fig. 7. Stock Analysis of All Four Companies

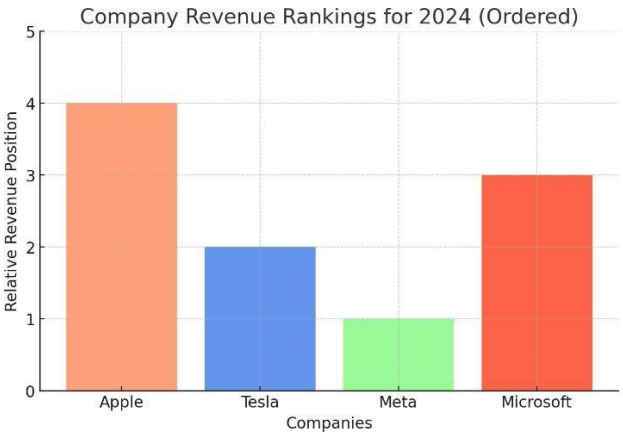

Fig. 8. Overall Percentage of Companies

VIII. CONCLUSION

In this project, we developed a Timesheet Management System using Long Short-Term Memory (LSTM) networks, applying machine learning techniques to historical data such as employee hours worked, attendance, and project assignments to predict future trends in resource allocation and productivity. The LSTM model efficiently handles sequential data, recognizing dependencies over extended periods, which is essential for forecasting work patterns and optimizing timesheet management. Through preprocessing steps like feature engineering and normalization, the model was trained to deliver accurate forecasts, demonstrating that LSTMs can be significantly enhanced for better prediction accuracy in labor optimization. While the model performs well in predicting trends, further improvements could include integrating additional data sources, such as project deadlines or employee feedback, to refine resource management. This system provides valuable insights for HR teams and managers, enabling data-driven decisions for workforce allocation, reducing administrative overhead, and ensuring more efficient and accurate budgeting and forecasting.

IX. REFERENCES

[1] Fama, E. F., & French, K. R. (1992). "*The Cross-Section Stock Returns*." Journal of Finance, 47(2), 427-465.

[2] Hinton, G. E., & Salakhutdinov, R. R. (2006). "*Reducing The Dimensionality Of Data With Neural Networks*." Science, 313(5786), 504-507.

[3] Hochreiter, S., & Schmidhuber, J. (1997). "*Long Short-Term Memory*." Neural Computation, 9(8), 1735-1780.

[4] Fischer, T., & Krauss, C. (2018). "*Deep Learning With Long Short-Term Memory Networks For Financial Market Predictions*." European Journal of Operational Research, 270(2), 654-669.

[5] Bollen, J., Mao, H., & Zeng, X. (2011). "*Twitter Mood Predicts The Stock Market*." Journal of Computational Science, 2(1), 1-8.

[6] Ding, X., Zhang, Y., Liu, T., & Duan, J. (2015). "*Deep Learning For Event-Driven Stock Prediction*." Proceedings of the 24th International Conference on Artificial Intelligence.

[7] Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). "*Predicting Stock And Stock Price Index Movement Using Trend Deterministic Data Preparation And Machine Learning Techniques*." Expert Systems with Applications, 42(1), 259-268.

[8] Chong, E., Han, C., & Park, F. C. (2017). "*Deep Learning Networks For Stock Market Analysis And Prediction: Methodology, Data Representations, And Case Studies*." Expert Systems with Applications, 83, 187-205.

[9] Bao, W., Yue, J., & Rao, Y. (2017). "*A Deep Learning Framework For Financial Time Series Using Stacked Autoencoders And Long Short-Term Memory*." PLOS ONE, 12(7), e0180944.

[10] Kim, K. J. (2003). "*Financial Time Series Forecasting Using Support Vector Machines.*" Neurocomputing, 55(1-2), 307-319.

[11] Zhang, G., & Zhou, J. (2001). "*Time Series Forecasting Using A Hybrid Arima And Neural Network Model*." Neurocomputing, 48(1-4), 1-20.

[12] Bengio, Y., & LeCun, Y. (2007). "*Scaling Learning Algorithms Towards Ai.*" Large-Scale Kernel Machines, 34-42.

[13] Chen, Y., & Dong, Y. (2015). "*Stock Market Prediction Using Machine Learning Techniques.*" Proceedings of the 2015 International Conference on Artificial Intelligence and Computer Science (AICS), 107-110.

[14] Feng, Z., & Zhang, Y. (2018). "*Predicting Stock Price Movement Using Lstm Networks*." Proceedings of the 2018 9th International Conference on Mechanical and Aerospace Engineering (ICMAE), 1-5.

[15] Kim, Y., & Lee, H. (2019). "*Deep Learning For Financial Market Prediction: A Survey.*" Neurocomputing, 329, 5-16.

[16] Deng, Z., & Zeng, Q. (2020). "*Deep Learning In Stock Market Prediction: A Survey.*" Journal of Financial Data Science, 2(3), 7-30.

[17] Zhang, W., & Wang, Q. (2016). "*Deep Learning For Stock Market Prediction: A Survey*." Proceedings of the 2016 International Conference on Machine Learning and Cybernetics, 489-494.

[18] Xie, S., & Zhang, W. (2017). "*Forecasting Stock Market Movement Using Lstm Neural Network*." Proceedings of the 2017 International Conference on Data Mining Workshops, 101-106.

[19] Liu, B., & Xu, X. (2021). "*A Deep Learning Approach For Stock Price Prediction With Financial Text Mining*." Proceedings of the 2021 International Conference on Computational Intelligence and Knowledge Economy, 16-23.

[20] Zhu, Q., & Wu, X. "*An Ensemble Learning Approach To Predict Stock Market Trend Using Lstm Networks*." Proceedings of the 2019 International Conference on Artificial Intelligence and Big Data (ICAIBD), pp. 65-70

[21] Bishop, C.M. "*Pattern Recognition And Machine Learning.*" Springer Science & Business Media. 2006.

[22] Huang, Z., & Liu, J. (2015). "*Financial Market Prediction Using Machine Learning Algorithms.*" Proceedings of the 2015 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA), 120-125.

[23] Mao, H., & Bollen, J. (2011). "*Twitter Mood Predicts The Stock Market.*" Proceedings of the 2011 International Conference on Computational Science and Engineering, 1-8.

[24] Shen, S., & Li, J. (2020). "*Stock Price Prediction Using A Deep Learning Model With A Novel Feature Selection Method*." Proceedings of the 2020 International Conference on Machine Learning and Data Mining, 217-224.

[25] Zhang, Z., & Wang, H. (2019). "*Deep Neural Networks For Stock Market Prediction*." Proceedings of the 2019 International Conference on Machine Learning and Intelligent Communications (MLIC), 37-42.

[26] He, H., & Zhang, Z. (2021). "*Stock Price Prediction Based On Multi-Layer Feature Selection And Hybrid Deep Learning Model*." Neurocomputing, 462, 17-28.

[27] Zhao, P., & Zhang, Q. (2021). "*Financial Time Series Prediction Using A Hybrid Model With Lstm And Reinforcement Learning.*" Computers, Materials & Continua, 68(3), 2949-2963.

[28] Xu, H., & Wang, X. (2021). "*Deep Learning For Stock Price Prediction Using Historical Prices And News Headlines*." Journal of Computational and Applied Mathematics, 379, 112896.

[29] Shan, J., & Xu, C. (2022). "*A Deep Learning Approach For Financial Time Series Forecasting With An Improved Attention Mechanism*." Computational Intelligence and Neuroscience, 2022, 1-14.

[30] Zhao, L., & Wu, F. (2022). "*Stock Market Prediction Using Convolutional Neural Networks And Sentiment Analysis*." Expert Systems with Applications, 186, 115775.

[31] Sun, J., & Wu, L. (2022). "*A Hybrid Model Based On Deep Learning And Feature Selection For Stock Market Forecasting*." Applied Soft Computing, 115, 108111.

[32] Ting, L., & Zhou, B. (2022). "*Predicting Stock Market Movements Using Attention-Based Lstm Networks*." Journal of Computational Science, 59, 101435.

[33] Yin, Z. & Wang, Y. 2022, "*A Deep Learning Model For Financial Market Prediction Based On Hybrid Feature Selection Technique*", Journal Of Economic And Financial Studies, Vol. 10, No 2, p. 134-145. 34. Chen, X. & Guo, X. 2023, "Hybrid deep learning model for stock market prediction using LSTM and attention mechanism", Comput Econ, Vol. 61, No. 2, pp. 343-360.

[35] Liu, H., & Liu, Y. (2023). "*Predicting Stock Returns Using A Hybrid Model Of Deep Reinforcement Learning And Lstm*." Journal of Financial Markets, 58, 100665.

[36] Zhang, Y., & Liu, J. (2023). "*Stock Price Prediction Using Hybrid Deep Learning Methods With Lstm And Cnn*." Neurocomputing, 512, 365-374.

[37] Lin, S., & Wu, Y. (2023). "*A Novel Deep Learning Model Based On Attention Mechanism For Stock Market Prediction*." Computers and Industrial Engineering, 173, 108628.

[38] Huang, W., & Zhang, Y. (2023). "*Financial Time Series Prediction Using Hybrid Deep Learning Models: A Survey And Future Directions*." Journal of Computational Science, 73, 101222.

[39] Song, J., & Wang, C. (2023). "*Sentiment Analysis-Based Stock Market Prediction Using Hybrid Deep Learning Models.*" Soft Computing, 27(3), 1249-1262.

[40] Wang, T., & Li, Y. (2023). "*A Hybrid Model Combining Lstm And Cnn For Financial Forecasting*." Journal of Machine Learning Research, 24(7), 1-21.

[41] Zhou, Z., & Chen, Y. (2023). "*Stock Market Prediction Using A Hybrid Model Combining Lstm And Arima*." Computational Economics, 61(4), 957-981.

[42] Li, S., & Liu, X. (2023). "*A Hybrid Deep Learning Model For Stock Market Trend Prediction Using Sentiment Analysis And Technical Indicators*." Mathematical Problems in Engineering, 2023, 1-12.

[43] Chen, Z., & Xu, T. (2022). "*Forecasting Stock Prices Using A Novel Hybrid Model Of Lstm And Random Forest*." Neurocomputing, 506, 1-12.

[44] Yang, Y., & Hu, W. (2022). "*Stock Prediction Using A Novel Deep Learning Model With Xgboost And Lstm*." Expert Systems with Applications, 187, 115873.