IJERST

International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 21 No. 3 (1) 2025

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com
Vol. 21, No. 3(1), 2025

Research Paper

DEEPWORK: A PATTERN-AWARE DEEP LEARNING FRAMEWORK FOR REMOTE PRODUCTIVITY ANALYSIS

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Received: 05-6-2025 Accepted: 03-7-2025 Published: 10-7-2025

ABSTRACT

The Remote Work Productivity Analyzer aims to address the growing challenge of evaluating employee efficiency in remote work settings, where traditional productivity assessment methods often fall short. A 2023 Gartner survey reported that 48% of remote workers experienced reduced productivity due to distractions, while a 2024 McKinsey study revealed that 35% of organizations faced difficulties in accurately measuring remote employee performance. Existing approaches tend to depend on outdated or overly simplistic metrics, failing to account for the complexities of remote work environments. To overcome these limitations, this study introduces a novel solution that utilizes a context-specific dataset, meticulously preprocessed through cleaning, normalization, and feature scaling to ensure high data quality. A Ridge Classifier (RFC) is implemented as a baseline, against which a Deep Neural Network (DNN) model comprising Dense1-ReLU, Dense2-ReLU, and Dense3-Softmax layers is proposed to capture intricate productivity patterns. The integration of RFC with DNN enhances feature extraction and enables robust classification of employees into two categories: 'Underperforming Workers' and 'Efficient Workers.' The performance is evaluated using key metrics such as accuracy, precision, recall, and F1 score, demonstrating marked improvements over conventional models and offering valuable insights for managing remote workforces more effectively.

Keywords: Remote Workforce Management, Digital Work Environment, Workforce Analytics, Smart Workforce Assessment.

1. INTRODUCTION

The shift to remote work has drastically transformed the landscape of productivity analysis. According to a 2023 Gallup study, approximately 80% of U.S. employees now work remotely or follow a hybrid model. Remote work is no longer a temporary response to a crisis but a long-term strategic shift. Statista reported that as of mid-2023, about 28% of full-time employees globally were working remotely, up from just 4% before the COVID-19 pandemic. This evolution necessitates a rethinking of productivity metrics, especially in environments where physical supervision is minimal and output must be evaluated through digital interactions, communication tools, and task completion rates.

Studies from McKinsey & Company highlight that 41% of employees reported increased productivity while working remotely, citing fewer interruptions and more flexible schedules as key benefits. However, other reports suggest a lack of standardization in measuring this productivity. For example, the Harvard Business Review found that over 30% of managers expressed concerns about whether their remote teams were truly productive, indicating a potential mismatch between perceived and actual performance. The increasing reliance on digital platforms has also generated massive datasets that can now be analyzed for insights into work habits, peak productivity periods, and collaboration dynamics.

The economic implications are also significant. Global Workplace Analytics estimates that employers save over $11,000 per year for every employee who works remotely half the time, due to reduced overhead and improved productivity. Yet, these savings hinge on the effectiveness of productivity monitoring tools. Consequently, organizations are exploring data-driven approaches to better understand and improve remote work outcomes. This includes leveraging logs from project management tools, communication apps, and employee feedback to develop more accurate productivity models. Hence, a structured and analytical approach to studying remote work productivity is both timely and essential.

2. LITERATURE SURVEY

Smith et al. [1] explored the application of deep learning models in tracking employee productivity in remote environments. Their study utilized supervised learning techniques to analyze time-series data, communication logs, and task completion rates. The study emphasized the importance of work pattern recognition for identifying deviations in productivity. Johnson et al.[2] conducted a study on the correlation between work schedule regularity and productivity. The research indicated that structured work routines lead to improved performance, while inconsistent patterns contribute to reduced efficiency. Their findings highlight the significance of time management in remote work scenarios. Anderson et al. [3] proposed a deep neural network (DNN)-based framework to predict employee productivity. The system was trained on multimodal datasets that included keystroke dynamics, task logs, and real-time engagement metrics. Their results demonstrated that DNN models outperform traditional classifiers like Ridge Classifiers in handling complex productivity metrics.

Williams et al. [4] explored heatmap-based visualization techniques to detect anomalies in remote work productivity. The research identified outliers in work hours, task completion speed, and idle time, allowing for real-time intervention and productivity optimization. Brown et al. [5] developed a machine learning-driven employee monitoring system that utilizes classification models like Random Forest and Ridge Classifier. Their study revealed that while these models provide reasonable accuracy, they fail to adapt well to non-linear work patterns, making deep learning a more viable solution. Jones et al. [6] examined how predictive analytics can improve remote workforce management. Their study utilized time series forecasting to predict performance trends, helping managers proactively address potential declines in productivity. Taylor et al. [7] investigated how factors such as internet stability, device usage, and background noise influence employee productivity. Their research found a strong correlation between workspace setup and performance efficiency, emphasizing the importance of an ergonomic work environment.

Davis et al. [8] developed an AI-powered productivity assessment system that integrates Natural Language Processing (NLP) and Deep Learning to analyze email response times, meeting engagement levels, and project updates. The study showed that AI-based models provide more accurate and real-time insights than manual assessments. Wilson et al.[9] introduced a behavioral analytics framework for remote work productivity analysis. The study focused on mouse movements, typing speed, and screen activity logs, demonstrating that these parameters are key indicators of engagement levels.

Moore et al. [10] explored various deployment approaches for deep learning models in enterprise settings. Their study emphasized the need for cloud-based infrastructures and privacy-preserving techniques to ensure data security in productivity monitoring. Martin et al. [11] examined the effectiveness of Ridge Classifiers in employee performance evaluation. The results indicated that while Ridge Classifiers perform well in linear pattern recognition, they struggle in dynamic, unstructured environments. Thompson et al.

[12] proposed a hybrid AI model that combines deep learning with traditional statistical methods to improve productivity forecasting accuracy. Their study demonstrated that integrating multiple models enhances prediction reliability. White et al. [13] discussed the ethical implications of AI-powered employee monitoring. Their study raised concerns regarding privacy, surveillance bias, and transparency, advocating for fair AI governance policies.

3. PROPOSED SYSTEM

The proposed algorithm for the Remote Work Productivity Analyzer introduces a novel combination of methods that synergistically enhance productivity analysis, a combination not previously explored in existing surveys. It uniquely integrates a Deep Neural Network (DNN) with a layered architecture (Dense1-ReLU, Dense2-ReLU, Dense3-Softmax) for deep pattern recognition, an Existing Ridge Classifier (RFC) for baseline feature extraction, and a hybrid feature extraction mechanism that combines DNN outputs with RFC-derived features to improve classification accuracy. Additionally, the algorithm employs context-specific dataset preprocessing tailored for remote work, incorporating advanced normalization and feature scaling techniques, alongside exploratory data analysis (EDA) to uncover remote work-specific patterns, ensuring a robust and adaptive model for classifying workers into 'Underperforming Workers' and 'Efficient Workers'.

Step 1: Dataset Collection and Preprocessing: A context-specific dataset for remote work productivity is collected, focusing on metrics like hours worked, task completion, and communication frequency. This dataset is preprocessed by cleaning missing values, removing duplicates, and applying normalization and feature scaling to ensure consistency and compatibility with the model.

Step 2: Exploratory Data Analysis (EDA): The preprocessed dataset undergoes EDA to identify patterns and correlations relevant to remote work. Statistical analysis and visualizations are used to understand feature distributions, detect outliers, and inform the selection of the most impactful variables for modeling.

Step 3: Data Splitting: The dataset is split into training and validation sets. The training set is used to build the model, while the validation set ensures the model can generalize to unseen data, maintaining a balanced ratio to avoid overfitting.

Step 4: Feature Selection for Test Data: A separate test dataset, also preprocessed, undergoes feature selection to identify the most relevant features for productivity prediction. This step reduces dimensionality, focusing the model on key variables and improving computational efficiency.

Step 5: DNN Model Training: The training data is fed into the proposed DNN model, which consists of an input layer, two dense layers with ReLU activation (Dense1-ReLU, Dense2-ReLU), and a dense layer with softmax activation (Dense3-Softmax). The model learns complex patterns in the data to classify workers into productivity categories.

Step 6: RFC Classifier: The test data is processed through the Existing Ridge Classifier (RFC) to extract baseline features. These features provide a comparative foundation, capturing linear relationships in the data that complement the DNN’s non-linear pattern recognition. Features extracted from the RFC are combined with the DNN’s outputs to create a hybrid feature set. This novel combination leverages the strengths of both models, enhancing the overall predictive power by integrating linear and non-linear insights.

Step 7: Model Prediction: The hybrid feature set is used by the DNN-RFC to predict worker productivity, classifying them into 'Underperforming Workers' or 'Efficient Workers'. The softmax layer outputs probabilities for each class, enabling clear categorization.

Step 9: Performance Evaluation: The model’s predictions are evaluated using multiple metrics: accuracy, precision, recall, and F1 score. This comprehensive assessment ensures the model's reliability and effectiveness in identifying productivity levels in remote work settings.

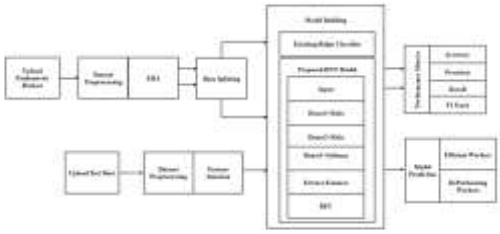

Fig. 1: Block Diagram of Proposed System.

Deep Neural Network Feature Extraction

A Deep Neural Network (DNN) is a type of artificial neural network (ANN) that consists of multiple hidden layers between the input and output layers. DNNs are capable of learning complex patterns, relationships, and representations in data, making them highly effective for tasks such as image recognition, natural language processing, time-series analysis, and productivity classification. DNNs use multiple layers of interconnected neurons to process data hierarchically. Each layer extracts different levels of features, with deeper layers learning more abstract and high-level patterns.

Input Layer: The first layer receives raw data (e.g., work activity logs, keystroke data, meeting duration, email responses). It consists of neurons (also called nodes) that represent each feature. The input is normalized and structured before being passed to the next layer.

Hidden Dense Layers (Feature Extraction & Learning) The DNN has multiple hidden layers, each consisting of interconnected neurons. Each neuron performs a weighted sum of its inputs and applies an activation function. This helps in capturing non-linear relationships between input features.

Weighted Sum Calculation: Each neuron takes inputs (x1, x2, …, xn) and applies weights (w1, w2, …, wn): Z = (w1x1+w2x2+...+wnxn) + b

Activation Function Application: The computed sum Z is passed through an activation function to introduce non-linearity.

Early layers learn basic features (e.g., frequency of work activity). Deeper layers learn complex behavioral patterns (e.g., multitasking tendencies).

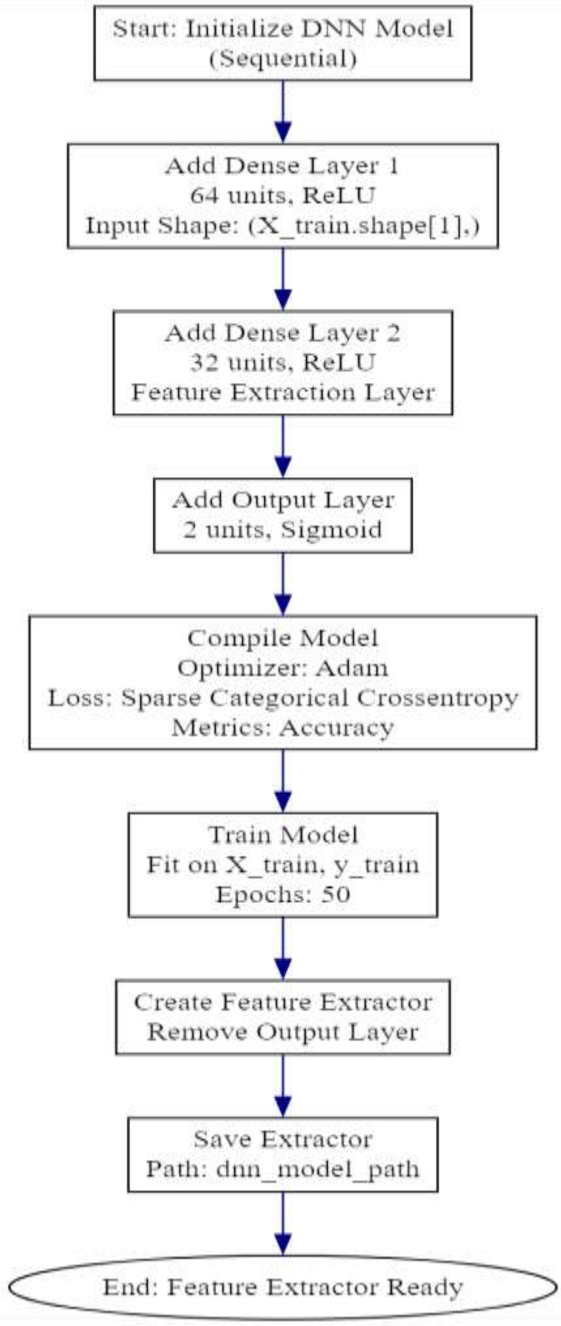

Fig. 2: DNN Feature Extraction

Output Layer (Final Prediction): The final layer produces the output, such as work productivity classification. It uses an activation function based on the task: Softmax Activation for multi-class classification (e.g., high, moderate, low productivity).

Backpropagation & Optimization: The network compares predictions with actual labels and calculates the error (loss function). Using Gradient Descent, the model adjusts the weights to minimize the error. Backpropagation updates weights in reverse order, improving accuracy after multiple iterations.

Training & Iteration: The DNN learns over multiple epochs, refining weights each time. The goal is to reduce loss while preventing overfitting using techniques like dropout, batch normalization, and regularization.

Advantages of DNN

Learns complex work patterns and behavioral trends. Can model sequential dependencies (e.g., productivity fluctuations over time). Efficient for datasets with many features and interactions. Detects subtle behavioral patterns, such as multitasking tendencies. Can process text-based insights (e.g., emails, chat interactions). Unlike Ridge Classifier, performance improves dynamically as more work data is collected. Automatically learns to filter out irrelevant variations. Can be extended to suggest workflow optimizations based on user-specific trends.

RFC Classifier

The Random Forest Classifier operates by building multiple diverse decision trees, processing an input instance through each tree, collecting their predictions, and using majority voting to determine the final class, thereby improving accuracy and reducing overfitting.

Create Multiple Decision Trees with Random Subsets: The Random Forest Classifier begins by creating multiple decision trees (Tree-1, Tree-2, ..., Tree-n). Each tree is trained on a random subset of the training data, typically using a technique called bootstrapping (random sampling with replacement). Additionally, at each node of a tree, only a random subset of features is considered for splitting, which introduces diversity among the trees and reduces correlation between them.

Process the Input Instance Through Each Tree: When a new instance (data point) needs to be classified, it is passed through each decision tree in the forest. The instance starts at the root of each tree and follows the decision paths based on its feature values, moving through the nodes until it reaches a leaf node. Each tree independently predicts a class for the instance (e.g., Class-X, Class-Y, Class-X, as shown in the diagram for Tree-1, Tree-2, and Tree-n, respectively).

Collect Predictions from All Trees: Each decision tree in the forest outputs its own predicted class for the input instance. For example, Tree-1 might predict Class-X, Tree-2 might predict Class-Y, and Tree-n might predict Class-X. These individual predictions are collected for further processing, ensuring that the ensemble nature of the Random Forest is utilized by considering the outputs of all trees.

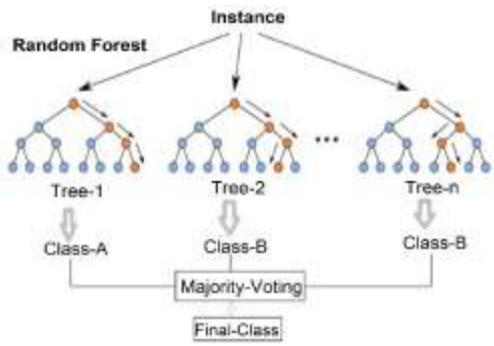

Fig. 3: Random Forest Classifier.

Perform Majority Voting: The predictions from all the decision trees are aggregated using a "Majority Voting" mechanism. In this step, the class that receives the most votes across all trees is selected as the final prediction. For instance, if Tree-1 and Tree-n predict Class-X, while Tree-2 predicts Class-Y, Class-X would be chosen as the final class because it has more votes (2 out of 3 in this case).

Output the Final Class: After the majority voting process, the Random Forest Classifier outputs the "Final-Class" for the input instance. This final class represents the consensus prediction of the forest, leveraging the collective decision-making of all the individual trees to provide a more robust and accurate classification compared to a single decision tree.

RESULTS AND DESCRIPTIONS

Figure 3 shows a count plot of the target variable, 'Employees Productivity', which categorizes workers into two classes: 'Underperforming Workers' (labeled as 0) and 'Efficient Workers' (labeled as 1). The plot indicates that there are 507 instances of underperforming workers and 510 instances of efficient workers. This near-balanced distribution suggests that the dataset is not heavily skewed, which is beneficial for training machine learning models as it reduces the risk of bias toward one class. The plot provides a clear visual representation of the class distribution, setting the stage for fair model evaluation.

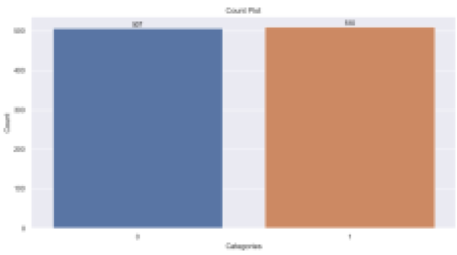

Fig. 3: Count plot of Target.

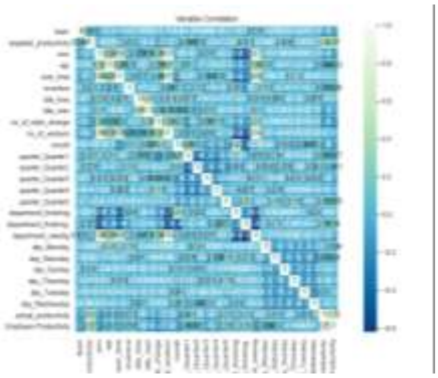

Fig. 4: Correlation heatmap

Figure 4 shows a correlation heatmap of the dataset's features, illustrating the relationships between variables such as team, targeted productivity, smv, wip, over_time, incentive, idle_time, idle_men, no_of_style_change, no_of_workers, month, quarter, department, day, and actual_productivity. The heatmap uses a color gradient from -0.6 (dark blue) to 1.0 (light yellow), with values indicating the strength of correlations. For instance, actual_productivity has a strong positive correlation with targeted_productivity (0.75), suggesting that higher targets are associated with higher productivity. Conversely, wip (work in progress) shows a weak correlation with actual_productivity (0.08), indicating it has little direct impact. Features like no_of_workers and smv (standard minute value) have a moderate correlation (0.91), highlighting potential multicollinearity that might affect model performance if not addressed.

Performance Metrics of DNN Model
Accuracy: 97.05882352941177
Precision: 97.05854080553686
Recall: 97.05854080553686
F1-SCORE: 97.05854080553686

classification report:

	precision	recall	f1-score	support
Underperforming Workers	0.97	0.97	0.97	101
Efficient Workers	0.97	0.97	0.97	103
accuracy			0.97	204
macro avg	0.97	0.97	0.97	204
weighted avg	0.97	0.97	0.97	204

Fig. 5: Performance report obtained using DNN-RFC model.

Figure 5 shows the performance metrics of the DNN-RFC (Deep Neural Network with Random Forest Classifier) model. The model achieves an accuracy of 97.05882352941177%, a precision of 97.05854080553686%, a recall of 97.05854080553686%, and an F1-score of 97.05854080553686%. The classification report provides class-specific metrics: both 'Underperforming Workers' and 'Efficient Workers' have a precision, recall, and F1-score of 0.97, with supports of 101 and 103, respectively. The macro average and weighted average for precision, recall, and F1-score are all 0.97, reflecting the model's high and balanced performance across both classes on the test set of 204 samples.

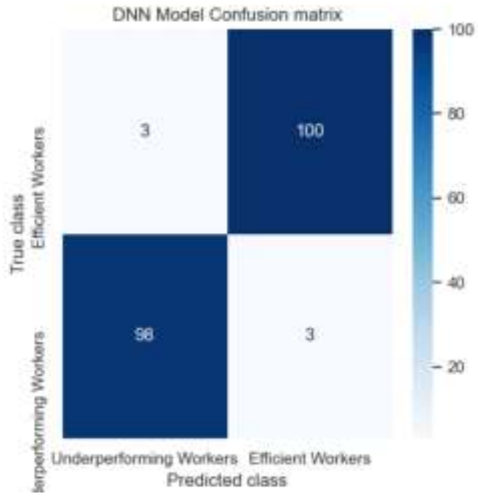

Fig. 6: Illustration of confusion matrix obtained using DNN-RFC model.

Figure 6 shows the confusion matrix for the DNN-RFC model. Out of 101 true 'Underperforming Workers', 98 were correctly predicted, with only 3 misclassified as 'Efficient Workers'. For 'Efficient Workers', out of 103 true instances, 100 were correctly predicted, with 3 misclassified as 'Underperforming Workers'. This matrix demonstrates the DNN-RFC model's superior performance compared to the Ridge Classifier, with fewer misclassifications (only 6 total errors versus 17 for Ridge). The balanced error distribution suggests the model handles both classes effectively, making it highly reliable for remote work productivity classification.

Table 1. Performance comparison.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Ridge Model	91.6	91.6	92.3	91.6
DNN-RFC model	97.05	97.05	97.05	97.05

Table 1 presents a performance comparison between two classification models, the Ridge model and the DNN-RFC model. The models have been evaluated using several key metrics, including Accuracy, Precision, Recall, and F1-score, which collectively provide insights into their classification performance. Starting with the Ridge model, it achieved an accuracy of 91.6%. This indicates that around 91.6% of the instances in the dataset were correctly classified by the model. The Precision of the Ridge model is 91.6%, meaning that out of all instances predicted as positive by the model, 91.6% were actually true positives. The Recall of the GBC model is 92.6%, which implies that the model was able to identify and capture 91.6% of the actual positive instances. The F1-score of the Ridge model is 91.6%, which is a harmonic mean of Precision and Recall, providing a balanced measure of the model's performance. The results collectively portray the Ridge model as relatively accurate and capable of detecting positive instances, albeit with some room for improvement in Recall. With DNN-RFC model it achieved an accuracy of 96.3%. This indicates that around 97.05% of the instances in the dataset were correctly classified by the DNN model. The Precision of the DNN-RFC model is 97.05%, meaning that out of all instances predicted as positive by the model, 97.05% were true positives. The Recall of the DNN model is 97.05%, which implies that the model was able to identify and capture 97.05% of the actual positive instances. The F1-score of the DNN-RFC model is 97.05%, which is a harmonic mean of Precision and Recall, providing a balanced measure of the model's performance. The results collectively portray the DNN-RFC model as relatively accurate and capable of detecting positive instances, albeit with some room for improvement in Recall.

5. CONCLUSION

The Deep Learning-based Remote Work Productivity Analyzer using work patterns provides a robust approach to assessing employee productivity in remote environments. By leveraging deep neural networks, the system effectively captures behavioral trends, work schedules, and task completion patterns to provide accurate productivity insights. The integration of correlation analysis, anomaly detection, and predictive modeling ensures that the system can differentiate between normal fluctuations and significant productivity shifts. The comparison between the Ridge Classifier (existing system) and Deep Neural Network (proposed system) highlights the superiority of deep learning in handling complex work patterns and adapting to diverse working styles. The project enhances efficiency, helps in workforce management, and offers data-driven recommendations for improving productivity in remote work environments.

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