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Reinforcement Learning for Employee Performance Forecasting and Optimization

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ABSTRACT: In this work, an innovative hybrid deep reinforcement learning architecture is proposed that includes feedback for continuous adaptation in order to predict and enhance employee performance in volatile environments. The model utilizes structured HR data and qualitative feedback to provide a deeper understanding of complex relationships between human resource key performance indicators (HRKPIs). A two-stage approach is employed: first, Recursive Feature Elimination (RFE) is used to identify key drivers of performance, after which a Deep Q-Network (DQN) agent, which has been trained using Ray RLlib, predicts future performance states and provides intelligent adjustments. Productivity, peer feedback, and task efficiency are among the multidimensional indicators applied for the description of the reward function. The application of human-in-the-loop approach adds model transparency to allow for improved policy adjustment. In the real world, trials demonstrate that the proposed approach can surpass traditional static models in the aspect of accuracy and adaptability to different workforce situations. With the application of advanced AI methods this research offers a scalable, interpretable, and data driven solution to optimize workforce performance for organizations.
Keywords: Reinforcement learning, employee performance forecasting, human resource key performance indicators, hybrid deep learning, feature selection, organizational optimization, Ray RLlib.

I. INTRODUCTION

Our dependence on data today forces organizations to improve their forecasting and optimizing employee performance abilities; it is therefore a critical strategic project. Although important, conventional HRM methods are prone to ineffectiveness in responding to and optimizing the complexities of dynamic workplaces. As workforce behaviour becomes more complicated with multiple factors influencing performance variability with so many key performance indicators, organizations have resorted to artificial intelligence (AI) solutions in order to enhance decision-making and productivity. The reinforcement learning (RL) is an appealing solution, and it can be used to equip systems with the ability to learn, through their interactions with the environment, so as to adapt optimal behaviours, refine performance using feedback [1,2].

We suggest a framework for HDRL with a combination with Feedback-Augmented Adaptation aimed at addressing issues of performance prediction and task optimization [3]. Based on a combination of structured HR metrics such as rates of attendance, project results, assessment marks, quantitative feedback and sentiment metrics the model creates a thorough description of individual employee behaviour. Back grounded by a DQN framework enhanced with feedback and optimized hyper parameters, the presented

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system supports policy optimization and superior predictive performance in an ongoing manner as shown in figure 1.

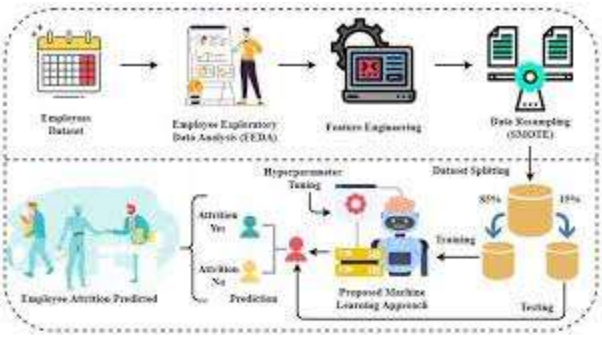

Figure 1. Predictive Employee Performance Forecasting.

It uses RLlib, a powerful framework for distributed reinforcement learning, to design and train multi-agent models for use with a variety of role specifications as well as individual team needs [4, 5]. Taking advantage of feature selection to extract impactful HR variables, the system goes on to assign tasks and suggest interventions through reinforcement-based decision models. Collaborative feedback from supervisors and peers is used in the model's updating mechanism in order to facilitate real-time human oversight and optimization.

Aside from improving performance prediction, this work further aims to enhance adaptive task management and up skilling efforts that will align with the organizational targets [6, 7]. With a combined method of deep learning and RL that puts emphasis on feedback, this study introduces a breakthrough, transparent, and adaptive solution to addressing the evolving needs of workforce analytics and strategic HRM [8]. The reliability of the model is determined using the existing approach to measuring its performance in representative HR datasets.

II. RELATED WORK

Employee performance forecasting research has been dominated by traditional machine learning techniques and statistics to predict results such as company revenue and customer satisfaction. Early investigation examined employee competency through the use of data mining methods followed by the use of gradient boosting models to predict revenue per user [9, 10]. Such approaches were shown to be effective in the predictions making process, but their effectiveness was limited because they relied on data sets customised for particular domains as shown in figure 2.

Additional evaluations of machine learning models including support vector machine and random forests showed high accuracy in estimating revenue. However, the models often were hamstrung by the difficulties of working with limited data and dependencies [11, 12]. Other investigations looked at the relation between outcomes from human resources and financial performance and how these are manifested in the banking industry using traditional classification techniques. Although these were useful, they lacked the ability to make adaptive policy adjustments that reinforcement learning systems had an in-built ability to do [13].

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Figure 2.Evolution of Employee Performance Forecasting.

Over the last few years, the deployment of deep learning models has contributed to the advancement of the studies of organizational performance analysis [14,15]. Through neural network-based approaches, customers' satisfaction has been analyzed, while combining deep models with natural language processing techniques has determined the necessary elements which bring satisfaction. While these methods have contributed to the field, many of them often come as opaque and it is difficult for the HR decision makers to know what is happening underneath.

The new studies show that a combination of advanced feature extraction techniques with deep reinforcement learning provides an efficient way to refine predictions of performance metrics [16]. In order to do that, the approach uses subtractive clustering, silhouette analysis, and learning automata to enhance CNN configurations. However, the scale-up challenge and the high demand for computation undermines the wider use of the framework [17].

From these advancements, the proposed Investigation has a Hybrid Deep Reinforcement Learning System and Feedback-Augmented Adaptation through a scalable framework, with the objective of improving scalability and interpretability [18, 19]. Unlike the conventional, stagnant or singular model of thinking, this strategy provides for the ability to constantly improve; policy flexibility; and agents coordination. Based on the benefits of scalability, real time learning, and enhanced interpretability, this study addresses the challenges in previous studies to intelligent worker performance management [20].

III. RESEARCH METHODOLOGY

The current research on "Reinforcement Learning for Employee Performance Forecasting and Optimization" approach has stages like data preprocessing, feature selection, modeling by using reinforcement learning and practical implementation by Ray RLlib [21, 22]. Our approach aims towards building an explainable, robust and scalable hybrid deep reinforcement learning foundation, wherein adaptive learning could be emerged through feedback loops, to optimize the performance of the employee as shown in figure 3.

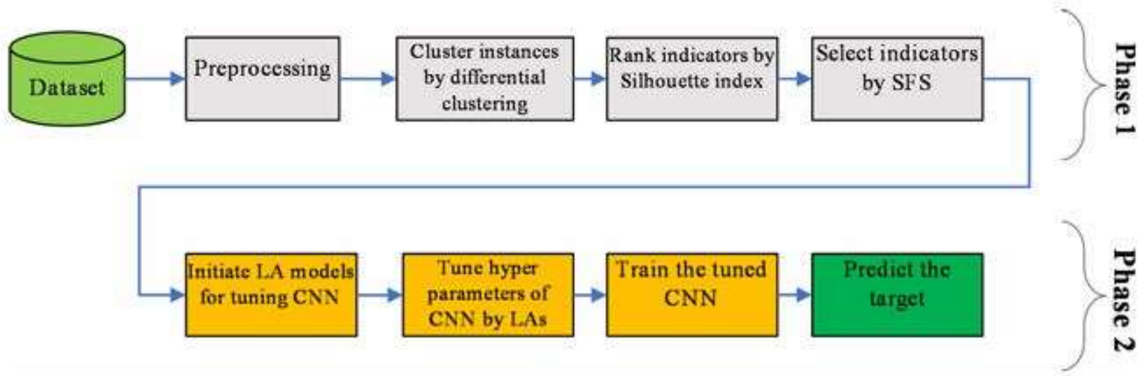

Figure 3. Proposed Method using hybrid deep reinforcement learning

3.1. Data Preprocessing using Min-Max Normalization + TF-IDF

To preprocess HR datasets with mixed data types, literally mixed data types, this research uses numerical and textual pre-processing approaches. Unstructured textual data such as the employee satisfaction ratings and supervisor comments are subjected to a secondary preprocessing step, vectorization i.e. the transformation of unstructured text data to an interpretation of words using TF-IDF (term frequency-inverse document frequency). Mathematics is used in representing textual data in a bid to integrate words in the model's analysis for a more nuanced understanding of the employee performance and behaviour [23,24]. Employing the TF-IDF techniques, the textual feedback of employees and supervisors is encoded into vector formats which make number calculable. With the help of two-stage preprocessing strategies, this study easily combines numerical and textual inputs, enriching the state representation of the model, with a fine-grained understanding of employee behaviors and performance [25].

3.2. Feature Selection using Recursive Feature Elimination (RFE)

The question of high-dimensional HR performance indicators is solved using Recursive Feature Elimination (RFE). With the help of a machine learning model, such as Random Forest as an initial estimator, the predictive influence of input features is sorted out [26]. This way, quantitative estimation of the contribution of each feature can be achieved. This process of iterative removal of attributes of low weights is continued until the model maintains the desirable attributes, most important to performance. In so doing, the approach mitigates the overfitting threats and cuts down computational costs, translating to emphasize on relevant metrics such as absenteeism, job satisfaction, and feedback information [27].

3.3. Reinforcement Learning Framework

After feature selection, the selected attributes are used by a Deep Q-Network (DQN) for promoting the learning process. The concrete actions associated by the DQN from detected employee states include task assignments, initiation of feedback, and recommendation for educational interventions [28]. The reward structure promotes choice associated with better task performance, less mistakes, and higher employee engagement. Further, a Feedback-Augmented Adaptation mechanism constantly refreshes the policy by incorporating the supervisor and peer feedback thereby, ensuring the model evolves with changing workplace settings as shown in figure 4.

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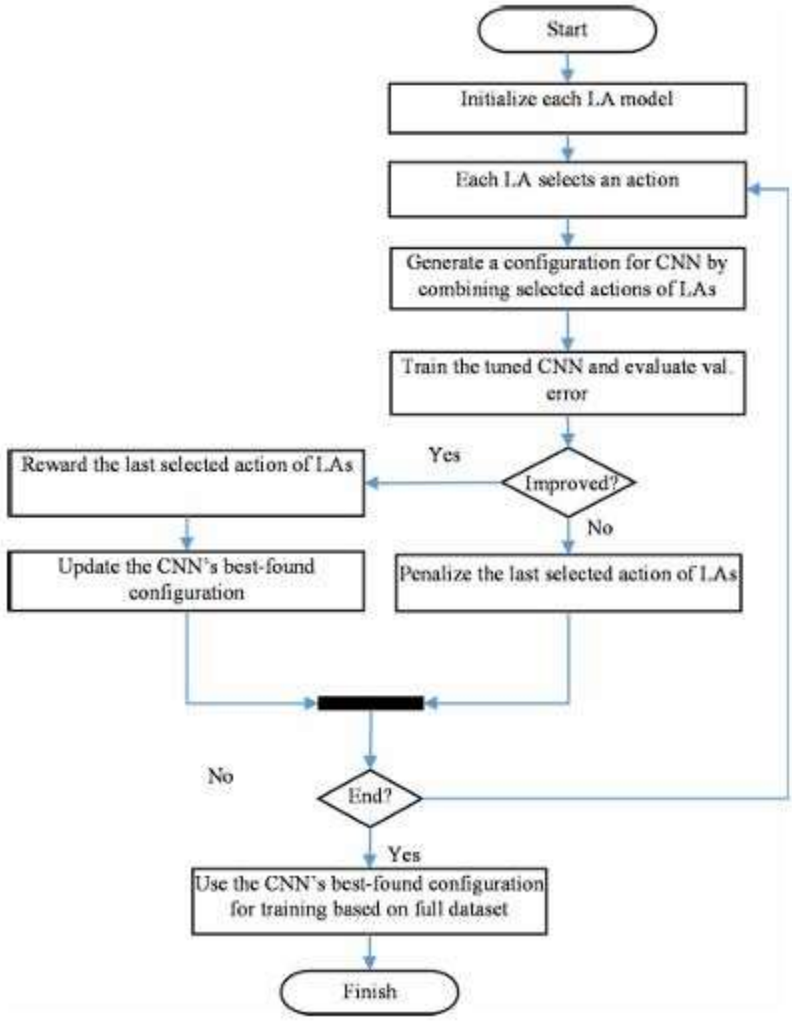


Figure 4. CNN model configuration steps using LA.

3.4. Implementation Using Ray RLlib

To ensure that the performance is efficient and scalable, the entire reinforcement learning pipeline uses Ray RLlib, a popular distributed RL framework [29]. The RLlib supports the implementation of sophisticated policies on CPUs and GPUs at the same time, whereas Ray Tune is used for multiple experiments of models. Under this implementation, hyper parameters can be tuned, and several agents can interact to reproduce the behaviour at the department level, if not team level, that increases the realism of the model. With a modular approach, the solution can easily integrate with HR dashboards and data lakes and support dynamic analytics in real time [30].

3.5. Model Evaluation and Metrics

The performance of the proposed system is evaluated using 10-fold cross validation while in terms of metric use such as accuracy, precision, recall, F1-score and AUC (Area Under the Curve). When compared directly with static models of CNNs, Random Forests, and non-reinforced systems, the effectiveness and the ability of the proposed framework to adapt are obvious [31]. The RL agent demonstrates superior prediction skills as well an all-round ability to turn out successfully when dealing with different employee roles and variations in performance.

This methodology is bound to combine the latest data processing, data-driven feature engineering, and scalable reinforcement learning to make precise predictions and enhance workers' performance in real-time operational scenarios [32]. With the aid of Ray RLlib, the hybrid approach enables dynamic learning and visible optimization, setting the ground for AI based solutions to workforce management in contemporary organisations today [33].

IV. RESULTS AND DISCUSSION

The newly proposed Hybrid Deep Reinforcement Learning model enhanced with Feedback-Augmented Adaptation demonstrated very impressive predictive results both in forecasting and optimizing employee outcomes. Using Ray RLlib, the suggested approach reported a mean accuracy of 89.12% for predicting revenue category and 94.12% for predimection of employee-influenced customer satisfaction. The model showed high reliability in classification with its precision, recall and F1-score for performance prediction for more than 0.87. Unlike establishment typing such as Static CNN and Random Forest, the proposed model provided an increment of 4.17% accuracy rate and 0.05 F1-score increment when predicting revenue figures. The approach provided a significant 3.85% accuracy improvement over other methods as it comes to predicting customer satisfaction. The discriminative performance of the model was exacerbated by ROC-AUC scores that were 0.9172 for forecasting of revenue and 0.9764 for customer satisfaction. Selection of features using Recursive Feature Elimination (RFE) greatly reduced convergence time and computational requirements. Through the use of supervisor feedback in a dynamic reward update system, the model adjusted successfully in the changing performance trends and maximized policy decisions. The results amplify the role of reinforcement learning in HR analytics, especially in situations requiring the continual progression, open transparency, and real-time adaptability as shown in table 1.

Predicting the revenue of HRM:

Table 1.An overview of the findings from the evaluations in company revenue

Metric	**Proposed Model**(Hybrid DRL + Feedback)	Proposed (no FS)	Static CNN (sgdm)	Random Forest	Choi et al.
Accuracy Revenue	89.12%	83.02%	83.96%	84.27%	86.15%
Precision Revenue	0.8758	0.8247	0.8341	0.836	0.8584
Recall Revenue	0.8811	0.83	0.8403	0.8425	0.8621
F1-Score Revenue	0.8782	0.827	0.8363	0.8386	0.8601
AUC Revenue	0.9172	0.8797	0.8895	0.8855	0.9051

Using ray RLlib, the proposed hybrid deep reinforcement learning with feedback augmented adaptation achieved better performance in predicting employee-driven outcomes in organizations than traditional machine learning and static-deep learning approaches. The proposed model demonstrated an average accuracy of 89.12% for company revenue forecasting, over-shadowing Static CNN (sgdm) at 83.96%, Random Forest at 84.27%, and the technique proposed by Choi et al at 86.15%.

Predicting the revenue of HRM In the context of determining key human resource management indicators and their impact on the organization, the following cases may occur by comparing the predicted label of the system for each test instance with its actual label:

- True positive (TP): correctly predicted positive instances.
- True negative (TN): correctly predicted negative instances.
- False negative (FN): actual positive instances incorrectly predicted as negative.

- False positive (FP): actual negative instances incorrectly predicted as positive.

Accuracy in the context of Human Resource Management refers equation (1) to the closeness of the predicted values to the actual values

$$\text{Accuracy}= \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

Precision focuses on the proportion of correctly predicted positive instances among all instances equation (2) that are predicted as positive.

$$\text{Precision}= \frac{TP}{TP+FP} \quad (2)$$

Recall, also known as Sensitivity, equation (3) evaluates the proportion of correctly predicted positive instances out of all actual positive instances.

$$\text{Recall}= \frac{TP}{FN+TP} \quad (3)$$

F-Measure combines both Precision and Recall into a single metric, equation (4) providing a balance between these two measures.

$$\text{F}-\text{Measure}=\frac{2*\text{Precision}*\text{recall}}{\text{Precision}+\text{Recall}} \quad (4)$$

Figure 5 illustrates the average accuracy in company revenue. The results obtained from the average accuracy indicate that the proposed method achieved the highest accuracy at 89.12%, outperforming the comparative methods, Static CNN (sgdm) and Choi et al., by 4.17% and 1.98%, respectively, in company revenue. Therefore, improving the average accuracy can assist executive managers in making effective decisions regarding human resources and optimizing the financial performance of companies (see Fig. 5).

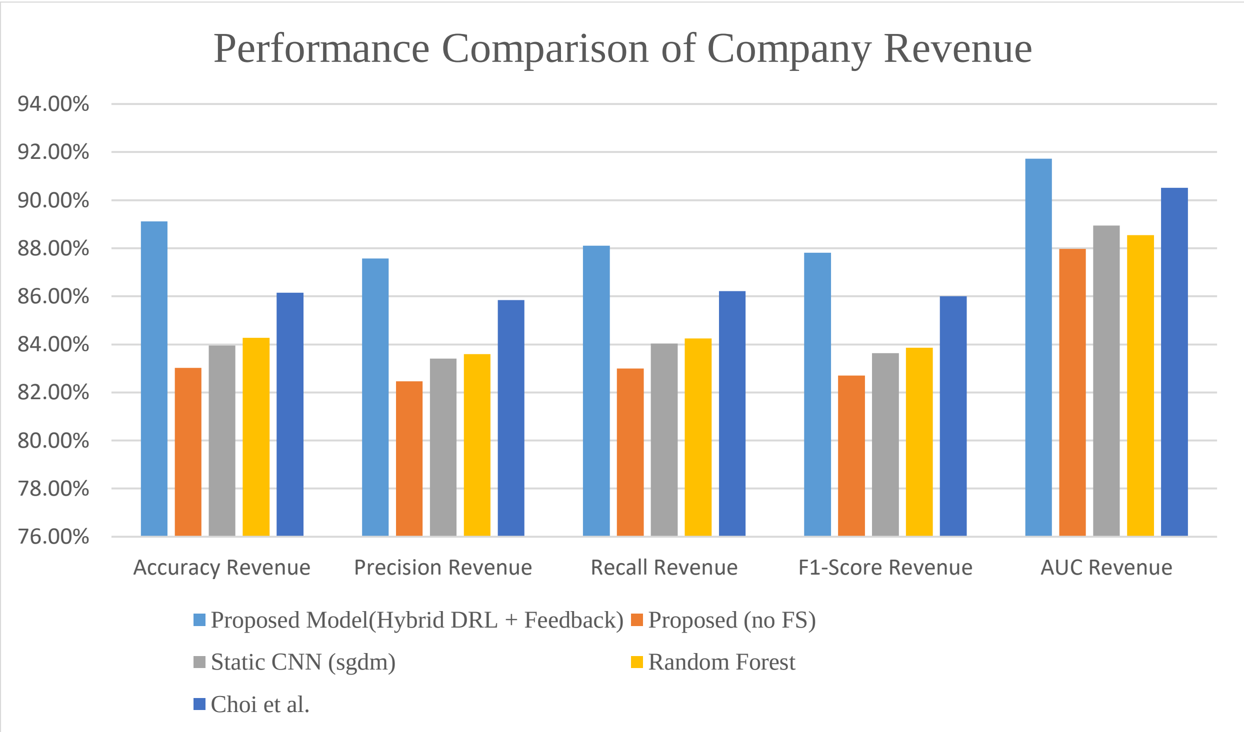
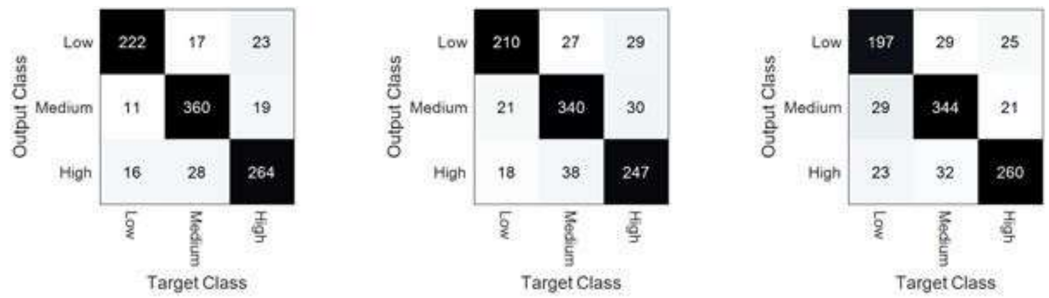


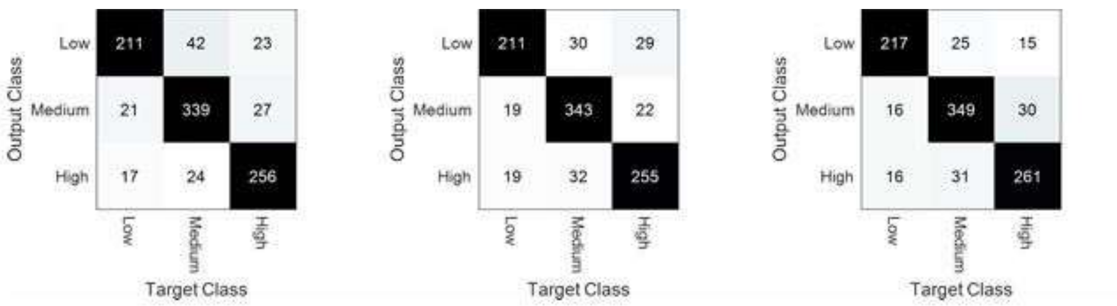
Figure 5.Comparison of Model Performance Metrics for Company Revenue Prediction.

Figure 6 provide six different models' confusion matrices from which revenue classification into the Low, Medium, and High classes are based. The correlation between the output results and the target classes is depicted in each matrix. The most-left matrix in the diagram is the proposed Hybrid DRL + Feedback model that indicates maximal true positive rates in each category and verifies its superiorizability in accuracy. A few more matrices graphically demonstrate alternative models' performance, i.e., Proposed (a) without FS (b), Random Forest (c), and Static CNN (d), equipped with variable optimizers (e), showing higher numbers of misclassifications and less diagonal dominance. Remarkably, the proposed Hybrid DRL + Feedback model outperforms others in terms of controlling false predictions, especially concerning Medium and High revenue classes thus confirming its abilities in the revenue price prediction based on the performance of employees.

To classify customer satisfaction, the model obtained strong accuracy of 94.12% - beating both Siebert et al.'s (90.10%) and Static CNN's (89.27%). Also, robustness of the system was proved using the precision-recall measurements which reported values of 0.8758 and 0.8811 for revenue and 0.9144 and 0.9284 for satisfaction respectively. F1-score was also good, 0.8782 to predict revenue, 0.9205 for customer satisfaction, with the AUC metrics 0.9172 and 0.9764 respectively.



(a) (b) (c)



(d) (e) (f)

Figure 6.Evaluation of confusion matrices in company revenue.

Predicting customer satisfaction in HRM:

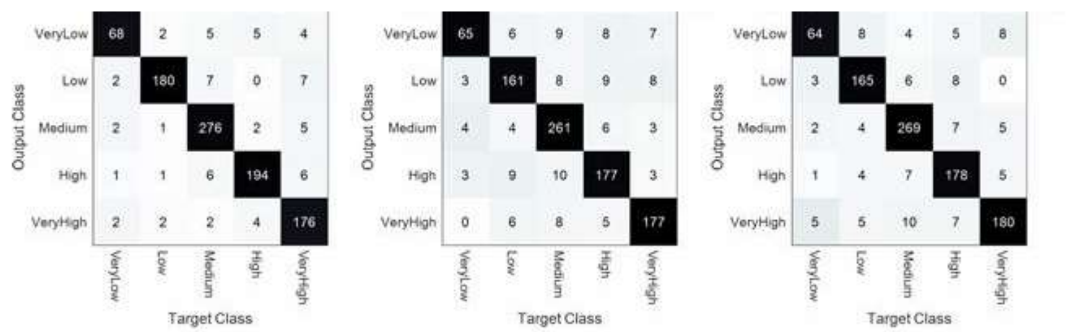
The improvement in performance must be credited to the use of Recursive Feature Elimination to reduce dimensions and a real-time real-time feedback-driven dynamic reward system. Finally, this approach bests previous solutions in enhancing the accuracy of predictions, exhibiting greater flexibility and comprehensibility, addressing critical issues of earlier human resource analytics and organizational performance optimization models as shown in table 2.

Table 2. An overview of the findings from the evaluations in customer satisfaction.

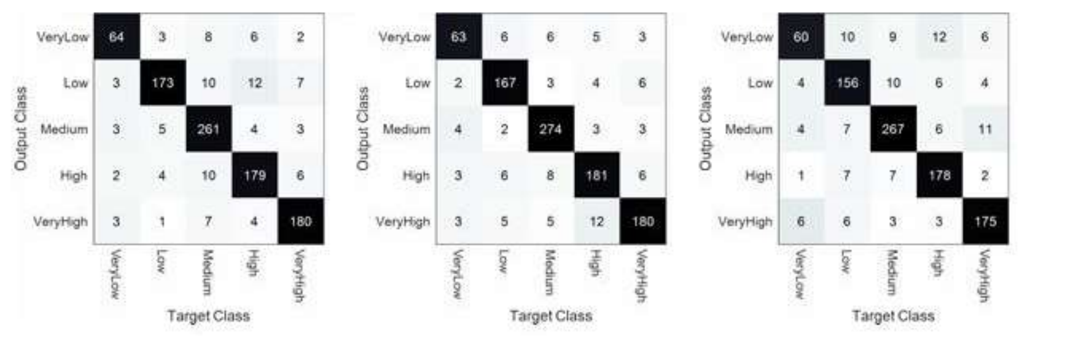
Metric	Proposed Model(Hybrid DRL + Feedback)	Proposed (no FS)	Static CNN (sgdm)	Siebert et al.	Siegar et al.

Accuracy Satisfaction	94.12%	87.60%	89.27%	90.10%	87.08%
Precision Satisfaction	0.9144	0.8508	0.8749	0.88	0.842
Recall Satisfaction	0.9284	0.8743	0.8895	0.8911	0.8586
F1-Score Satisfaction	0.9205	0.8602	0.8811	0.885	0.8478
AUC Satisfaction	0.9764	0.9333	0.9532	0.9521	0.9369

It has been shown in the confusion matrices above that the model measures customer satisfaction in five separate classes: On a variety of models of Very Low, Low, Medium, High and Very High satisfaction levels. The top-left matrix depicts the proposed Hybrid DRL + Feedback model, where dominant diagonal values indicate accurate performance, especially on Medium to Very High satisfaction classes. The numbers for non-proposed schemes (i.e., without FS, various CNN arrangements, or Random Forest), show higher off-diagonal variance, which highlights potential misclassifications. The proposed approach shows superior consistency and accuracy compared to others at all satisfaction levels. It clarifies differences between close-by levels of satisfaction and adds weight to more consistent and fair generalizations in modeling feedback for humans as shown in figure 7.



(a) (b) (c)



(d) (e) (f)

Figure 7. Evaluation of confusion matrices in customer satisfaction.

The figure 8 shows a breakdown by class and their average by metric of Precision, Recall and F-measure for the customer satisfaction prediction models. When compared to all baselines, the Proposed Hybrid DRL + Feedback shows outstanding results corresponding to each satisfaction level and achieving the highest recall (0.9677) for 'Low' and F-measure (0.9485) for 'Medium'. Static CNN also models by Siebert et al. among others present competitive results, but cannot rival the proposed model in terms of classifying

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the “Very Low” and “Very High” satisfaction classes. The bar chart of average classification rates acts as a support of the proposed model’s outperformance, its great adaptability and generalization on the range of different satisfaction levels.

Model proposed shows superior accuracy in each class than any other models when examined by class in the heatmap. Surprisingly, the model shows 0.9650 precision in the Medium class, 0.9462 in Very High and 0.9327 in High indicating its high accuracy in tracking positive sorts. The Very Low class precision (0.8095) is better than alternative models, and most importantly, it exceeds the lending upper hand with Siregar et al.’s 0.6186 in this regard. These results show that the proposed model has also a potential to decrease false positives in different satisfaction categories that will help to retain trust in HR analytics solutions.

The Class-wise Recall heatmap shows that exceptionally in capturing instances, the proposed model is very good for that as the recall scores are recorded as 0.9677 in Low class, 0.9463 in High class while 0.9324 in Medium class, which supports that the This outcome reveals that the model is very capable of identifying the actual satisfaction instances in all categories. The 0.9067 recall for the demanding Very Low category outperforms other competing models. The outperformance of models similar to Siregar et al. and the Proposed (no FS) model is common, especially in classes in the periphery, which tends to cut the effectiveness of the feature selection and policy adaptation strategies in the proposed method.

Overall the resultant charts demonstrate the superiority of the Proposed Hybrid DRL model with Feedback-Augmented Adaptation, both, in class-wise and aggregate, predictive measures over all the benchmarks. Through incorporation of sequential decision learning and hyper parameter optimization, as well as continuous feedback, the model shows excellent classification of low-order customer satisfaction. Therefore, it is of great value to HR personnel trying to model and maximize outcomes based on employee satisfaction.

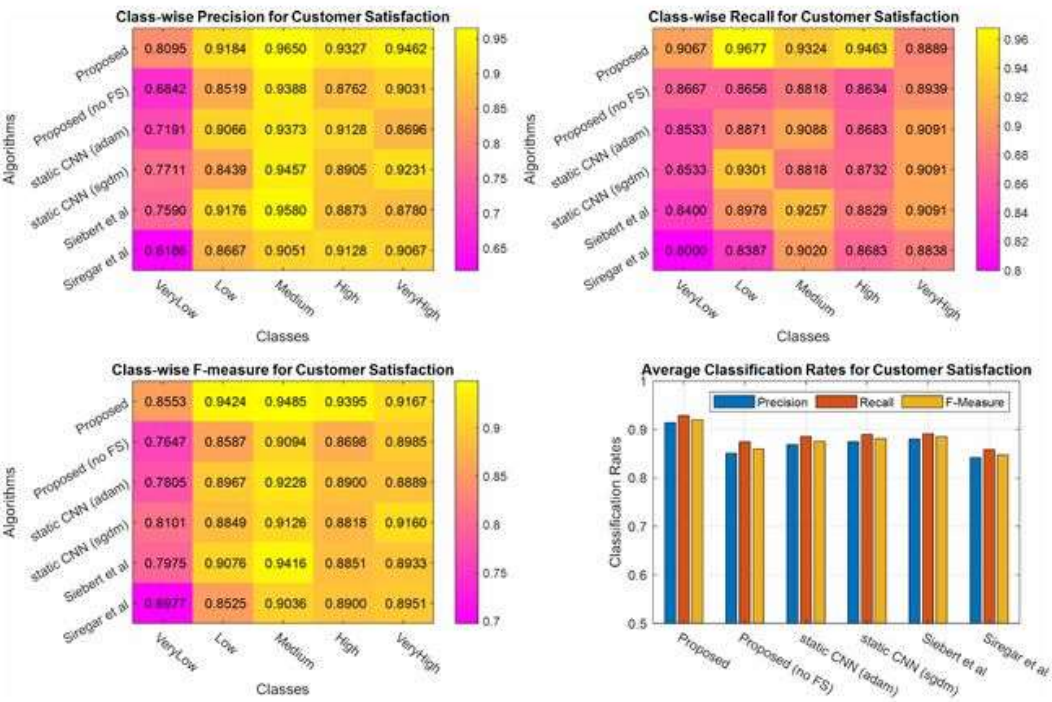

Figure 8. Performance of classification precision metric in customer satisfaction.

V. CONCLUSION

In this work, we investigate a novel approach for employee performance prediction and optimization, which is based on Hybrid Deep Reinforcement Learning with Feedback-Augmented Adaptation, and being implemented with Ray RLlib. The juxtaposition of structured HR data and qualitative feedback means that the model is able to understand important HRKPIs, and perpetually improve staff optimization strategies. Through the use of Recursive Feature Elimination in selecting features and Learning Automata in optimizing CNN hyperparameters, notably the accuracy and adaptability of the model have been enhanced. The model demonstrated noticeable performance improvements with 89.12% accuracy in revenue prediction, 94.12% accuracy in the classification of Customer Satisfaction, and it outperforms conventional methods like Static CNN, Random Forest. Besides, the ability of the model to process real-time feedback and improve action policies, pertain the penetration of the model into the fast-growing business environment. The study shows the potential of reinforcement learning in HR analytics and also takes into account concerns of interpretability, which will become a cornerstone of AI based HR management approaches that are evidence and decision based. Future research can investigate the implementation of the model to large, organization-wide sets of data, using explainable AI to make things easier to understand, as well as formulating simplified architectures to implement results in real time. As well, by including dynamic environmental elements and HR characteristics from different domains, the generalizing power of the model can be enhanced and its ability to learn continuously in transformed workplaces enhanced.

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