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Article

An Innovative Approach to Predicting Employee Attrition through Optimized Neural Mining and Advanced Classification Techniques

D. Senthil Kumar [1], S.Sivanesh[2*], G.Mani[3], K. Rajesh Kambattan[4]

[1]Department of CSE, University College of Engineering, Anna University, Tiruchirapplli, Tamil Nadu, India
[2]Department of CSE, University College of Engineering, Anna University, Panruti, Tamil Nadu, India
[3]Department of CSE, University College of Engineering, Anna University, Kanchipuram, Tamil Nadu, India
[4]Department of CSE, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Tamil Nadu, India
[1]desent07@gmail.com,2diggfacts@gmail.com, 3gmani1879@gmail.com, 4rajesh.kambattan@gmail.com

Abstract: Employee turnover is a slow process of staff loss because of reasons such as retirement or personal choices, and it is not always replaced with a like in a similar time frame. In the context of organizations, appropriate forecasting of attrition is essential to ensure that the organizations retain talented personnel to aid in strategic planning of the workforce. The current paper proposes a new deep learning model, Optimized Neural Mining and Classification Logic (ONMCL) to enhance attrition prediction of employees. ONMCL combines state-of-art in neural network potentials and methodical pre processing of data, which could help unearth patterns in workers conduct and turnover proclivities. Traditional Logistic Regression (LR) is used to model it against so as to verify performance. Whereas LR had an accuracy of 93% in training, ONMCL performed better with accuracy more than 96%. Main drivers of attrition and their interdependencies are also discussed in the study. Findings demonstrate that ONMCL not only increases the accuracy of prediction but also offers organizations greater predictive insights relative to the causes of attrition with respect to the provision of more stable and actionable resource in respect of proactive advance planning retention of employees within organizations.
Keywords: Employee Attrition, Deep Learning, Neural Mining, Classification Logic, Predictive Modeling

1. Introduction

The digital economy today is built on the abilities, drive, and loyalty of the workforce and a company that performs best using its employees is highly likely to succeed. The level of innovation, quality of work output and a company or organizations competitiveness in the future directly relate to their productive employees [1]. Nonetheless, employee attrition which can be explained as the loss of staff through voluntary or involuntary exit of employees in an organization, continues to pose a big problem. The attrition affects group bonding, the flow of projects, customer-related issues, and costs it in terms of its recruiting, onboarding, and training. The economic cost is dramatic and the non-economic cost of the exits of experienced or high potential people are even more lethal. Beyond the replacement cost, attrition also erodes organizational and institutional knowledge and it can leave holes along the ranks in leadership pipeline and slows down other important initiatives. Although a certain degree of attrition is normal, unmanaged or even unforeseen turnaround could cripple the focal areas of business processes. An estimation or prevention of the attrition of employees has thereafter turned out to be a strategic focus of the HR groups and the top management alike.

The causes of employee turnover are multi-dimensional and sometimes they are interrelated with both professional and personal reasons. The most frequently reported causes include low pay, job dissatisfaction, absence of a career development, work-life imbalance and poor relations with managers. But these variables are not independent of each other, they instead affect each other in small, non-linear manners. Standard HR systems and statistical models are usually not able to take account of these dependencies. Viable approaches such as Logistic Regression (LR) and Decision Trees have been common in attrition forecasting that normally yields comparably low accuracy (8593%) and unappreciable interpretability [2]. What is more, reactive methods are used by many organizations, which is being involved only when high value talent has walked away. It is obvious that a change involving predictive and proactive measures capable of not just predicting the possible exits but also the identification of the reasons as the basis of such prediction is needed. It is here that machine learning in general and deep learning in particular offers a chance to radically change the way that attrition is understood and dealt with.

In the study, a new neural mining and classification logic deep learning architecture are proposed, known as Optimized Neural Mining and Classification Logic or ONMCL. Compared with other traditional models which assume the presence of flat and independent features, ONMCL has been developed to enable the learning of the hierarchical and abstract nature of feature representations that are more realistic in HR contexts. It achieves it with the help of a multi-layer neural network structure, preprocessing pipelines and hyperparameter tuning functionality namely the learning rate adjustments based on the OptiANN-LR model that was suggested by Sudharson et al [3] and delivered a strong performance improvement in the field of medical prediction. On applying analogous optimization methods to HR data, ONMCL reaches a better than 96% accuracy in making predictions, outdoing not only classical ML models but also simple neural networks. This model also combines dropout regularization and tuning of the activation functions to counter the effect of overfitting and improve generalization of the data on unseen data.

Another rising issue related to HR analytics that OMNCL framework will answer is data privacy and interpretability. The sensitivity of employee data used to create predictive models has to be resistant to privacy risks. ONMCL relies on federated learning methods proposed by Sudharson et al. [4] and is built with the privacy-sensitive data processing procedures. It is not fully federated even though its modular design will enable it to be implemented at a distributed environment. In addition to this, the model is explanatory- it uses the feature attribution mechanisms to determine how much each prediction was affected by each factor. This makes it transparent and helps in the practical intervention of HR. As another example, when job role stagnation and a high overtime frequency are pinpointed by the predictive model as the most significant factors that contribute to an on-the-edge attrition scenario, the corresponding HR managers will now be able to develop tailored interventions, such as internal mobility options or the redistribution of work tasks, to eliminate turnover. Such diagnostic ability does not only make ONMCL a prediction engine but also a decision-making tool in terms of sustainable workforce planning.

In favor of such direction is the increasing number of studies considering neural networks and attention mechanism in HR applications. Another example would be the hierarchical attention model suggested by Jain et al. [5] to forecast the trends of employee performance indicating that the attention-based models can be successfully applied to the sequential behavior detection in the workplace data. The same was observed by Hamja et al. [6], who found out that the application of explainability tools in prediction models offers practical insights and hence improved strategic results. ONMCL is based on these developments and integrates predictivity with the explanations of results and scalability. It includes attention-like reasoning in its opaque strata to enhance the incorporation of significant variables like job satisfaction, years in company and promotion in recent times. These improvements make sure the system does not work as a black box which is an indispensable factor to implement the system in sensitive HR climate.

Summing it all up, employee exit is no longer at least an HR-Hassle, it is a major challenge to the entire organization, and it directly affects profitability, stability, and competitiveness. With the current dynamic and volatile nature of the global talent market, it is not enough to have a tool that predicts attrition; companies need a tool that explains attrition. The ONMCL framework that will be proposed will fill this gap by providing a deep learning solution that incorporates all three concepts of optimization, interpretability, and scale. Combining the ideas of these recent works in federated learning, neural tuning, and HR performance analytics, ONMCL allows shifting an organization to proactive talent retention planning instead of a reactive talent management approach. This background provides some context to the other sections where the architecture, process, evaluation, and consequences of ONMCL are going to be discussed in details.

2. Related Works

Deep learning methods using optimization have also demonstrated significant potential with respect to employee attrition prediction. Habous et al. [7] crossed supervised classification models using HR analytics and revealed that more powerful learners are better than less simple models when processing complex datasets of the workforce. Riding on this, Subrahmanya et al. [8] developed the Improved Sparrow Search Algorithm-based Deep Belief Network (ISS-DBN) which was more effective compared to traditional deep frameworks because its classification accuracy was increased and converged quicker. In this contribution the effectiveness of metaheuristic optimization as a part of the deep learning designs was verified in terms of recognizing complex associations of features offered in the HR data.

Simultaneously, predictive models have been highlighted in terms of interpretation requirement. Pathi et al. [9] proposed an explainable framework in attrition prediction using the feature attribution techniques to identify the most important variables according to which the HR managers can develop specific retention policies. On the same note, Mitravinda et al. [10] integrated machine learning and explainable decision rules, thus building user-trust and facilitation of practical application of such knowledge in an organization.

Ensemble learning has also proved to be a very viable solution towards achieving greater performance in the prediction of attrition. Alshiddy et al. [11] implemented a two-layer nested ensemble model based on the IBM HR Analytics Employee Attrition & Performance dataset and demonstrating statistically significant gains over a Random Forest baseline function (accuracy measured to be 94.53% and AUC 98.5). Chung et al. [12] also contributed to increases in prediction accuracy by using a stacking ensemble of the Random Forest and Artificial Neural Networks that increased accuracy to 97.6 percent and disclosed overtime, interpersonal satisfaction, and environmental satisfaction as the primary drivers in attrition.

The ability of the traditional machine learning methods to provide an interpretable solution keeps them as useful benchmarks because they are relatively inexpensive in terms of computation cost even though modern methods are now comparable to them. Padmaja et al. [13] tested some ML and deep learning models on the IBM Kaggle dataset focusing on their accuracy compared to some traditional classifiers, the K-Nearest Neighbors algorithm performed the best among traditional classifiers with an accuracy of 84%, but it had the issue of frequent retraining because of the data drift. In an attempt to deal with class imbalance in HR datasets, Shobhanam et al. [14] used and compared Synthetic Minority Oversampling Technique (SMOTE) with Random Forest classifier and a Random Forest classifier directly with cross-validation reaching 98.83 as the highest subset of all results and increasing sensitivity on the validation data only slightly.

Trade-offs among the modeling techniques have also been assessed comparatively. After massive preprocessing, Mansor et al. [15] compared Decision Tree, Support Vector Machine and Artificial Neural Network classifiers and an optimized SVM was the most accurate yielding 88.87%. Gurler et al. [16] continued these comparisons and included features selection, hyperparameter optimisation and SMOTE-Tomek Links resampling to the deep learning architectures and found that deep methods displayed a benefit over conventional ML methods as a whole.

Explainable AI (XAI) techniques have also been built recently to enhance adoption and transparency. Das et al. [17] used SHAP and LIME methods of explaining which attributes prevented quick attrition, with the accuracy of predictions reaching about 96 percent, and identifying a set of essential features that can be tackled by human resource initiatives. The latest research by Varkiani et al. [18] in Expert Systems with Applications joined the prediction of attrition with the analysis of its determinants and directly discussed the issue of class imbalance and the business needs of measuring the employee turnover, therefore offering a rigorous and practically applicable framework of HR analytics.

All these studies serve to demonstrate that optimization-based deep learning, ensembling, and the explainability of models can contribute majorly to predictive quality and usability. Nevertheless, currently, there is no single method that combines optimization-based deep architecture, robust ensemble, and countermeasures to data imbalance, together with inherent explainability and composability. The proposed Optimized Neural Mining and Classification Logic (ONMCL) model will try to close this ignorance.

3. Materials and Methods

The suggested Optimized Neural Mining and Classification Logic (ONMCL) model is intended to discover hidden threats of the employee turnover potential using a systematic pattern involving highly intelligent antecedence, composite class treatment, optimal neural network shaping, and all-inclusive performance appraisal. There is a distinct workflow followed by utilizing data acquisition; then, through the evaluation of existing models, the prediction capacity of the model is achieved, i.e., increased; and the interpretability of the models is established i.e., improved.

3.1. Data Collection

The data retrieved in this research belongs to Kaggle repository of HR Analytics repository and contains 10000 rows of data on the employee set, out of which 5647 cases represent attrition and 4353 cases represent retention. The demographic variables, employment history, work environment factors, and performance indicators are incorporated in each of the records and allow a multidimensional outlook on the workforce characteristics.

Let the dataset be defined as:

$$D = \{(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)\}$$
(1)

where xi is the feature vector of employee i, and yi in {0,1} is the attrition label (1=attrition,0= no attrition).

3.2 Data Preprocessing

3.2.1 Data Cleaning

Less significant features or features having constant values like Employee Count, Over18, Standard Hours and Employee Number were discarded to trim down dimensions and noise.

Assume that X0 is the initial set of features, and C= {C1, C2, C3, C4} is the constant feature set, then the cleaned set of data Xc can be produced as:

$$X_c = X_0 \setminus C$$
(2)

3.2.2 Normalization

In order to have equal importance of all the numeric variables, Min-Max normalization was used:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$
(3)

The normalized value x', x is the original value of the feature, xmin and xmax are the minimum and maximum values of that feature column.

3.2.3 Categorical Encoding

The categorical variables (Department, Business Travel, Gender, etc.) were converted to numbers, through the One-Hot Encoding, which is defined as:

$$X_n = Encode(X_c)$$
(4)

where Xn, Xc is the fully numerical data to train the model.

3.3 Feature Selection

The calculation of feature importance was done to leave behind the variables relevant to prediction. The attrition probability response with respect to the model a is given as:

$$S = \beta_0 + \sum_{i=1}^{n} \beta_i X_i \quad (5)$$

Where β0 is the intercept, if βi denotes the weight of importance of the feature Xi that is learnt and n denotes the number of features selected. Features whose contribution to importance was practically zero were omitted.

3.4 Data Balancing

The dataset had moderate class imbalance, and therefore Synthetic Minority Oversampling Technique (SMOTE) was used to create synthetic minority class samples:

$$xnew = x_{minority} + \delta \times (x_{nearest} - x_{minority}) \quad (6)$$

where δ ∈ [0,1] is a random variable, xminority is a minority sample, and xnearest is a nearest neighbour of xminority.

3.5 Model Configuration and Optimization

The newly suggested Optimized Neural Mining and Classification Logic (ONMCL) system consists of a multi-layer feedforward neural network structure combined with an objective-driven strategy of hyperparameter optimization conducted by a metaheuristic algorithm search. In the predictive model, three fully linked concealed layers are structured, the Rectified Linear Unit (ReLU) activation functionality is used, which can be explained as

$$h^{(l)} = max(0, W^{(l)}h^{(l-1)} + b^{(l)}) \quad (7)$$

in which W(l) and b(l) represent the weight matrix and bias vector of the lth layer and h(l-1) is the output of previous layer. The dropout structures are placed after every hidden unit to avoid overfitting whereby a fraction pd of the neurons is switched off randomly in the training process. The output layer contains one single neuron and the sigmoid activation function that is used to express it in the form of:

$$\hat{y} = \sigma\left(W^{(L)}h^{(L-1)} + b^{(L)}\right), \sigma(z) = \frac{1}{1+ e^{-z}} \quad (8)$$

which returns a probability of employee attrition. The prominent novelty of ONMCL is that it uses the Improved Sparrow Search Algorithm (ISSA) to tune hyperparameters in an automated process. Instead of using such traditional tools as grid search or random search, ISSA actively samples the search space to identify the best values of potentially important parameters, such as the learning rate (η), batch size (Bs), number of hidden neurons per layer (Hl), and dropout probability (pd), or the L2 regularization coefficient (λ). The ISSA candidate solutions corresponds to a hyperparameter configuration Si={ηi, Bsi, Hli, pdi, λi} that are potential configurations of the hyperparameters.

First, this optimization process starts by a starting point population of sparrows, which is measured through a fitness function that is set as the negative validation loss of the ONMCL model:

$$F(S_i) = -L_{val}(S_i) \quad (9)$$

The ISSA, in turn, revises the locations of the sparrows based on behavioral tactics on the basis of natural polling. Exploration is carried out by producers whose position is then revised.

$$X_i^{t+1} = X_i^t \cdot exp\left(\frac{-i}{\alpha \cdot T}\right)$$
(10)

in which, alpha is a control parameter and T is the maximum number of iterations. Scroungers utilize the opportunities which have been provided by the producers with the use of the update with promising areas which are discovered by the producers themselves.

$$X_i^{t+1} = Q \cdot exp\left(\frac{X_{best}^t - X_i^t}{i^2}\right) \tag{11}$$

Q is a normally distributed random number. Sparrows perform an escape maneuver when potential dangers are perceived, or when in poor solutions.

$$X_i^{t+1} = X_{best}^t + \beta \cdot \left|X_i^t - X_{worst}^t\right|$$
(12)

where the intensity of escape is controlled by β. This is an iterative procedure which is repeated until the termination criteria is obtained; this will either be convergence or the number of iterations reached.

Incorporation of ISSA to ONMCL provides a good exploration and exploitation trade-off of the hyperparameter search space. Such method will converge much faster, minimize chances of getting trapped in local minima and produce a hyperparameter setting that can both maximize the accuracy of the predictive portion of the model as well as its generalization potential. Experimental findings show that the ISSA-tuned ONMCL outperforms manually tuned neural networks in terms of classification accuracy proving the efficiency of the given optimization strategy.

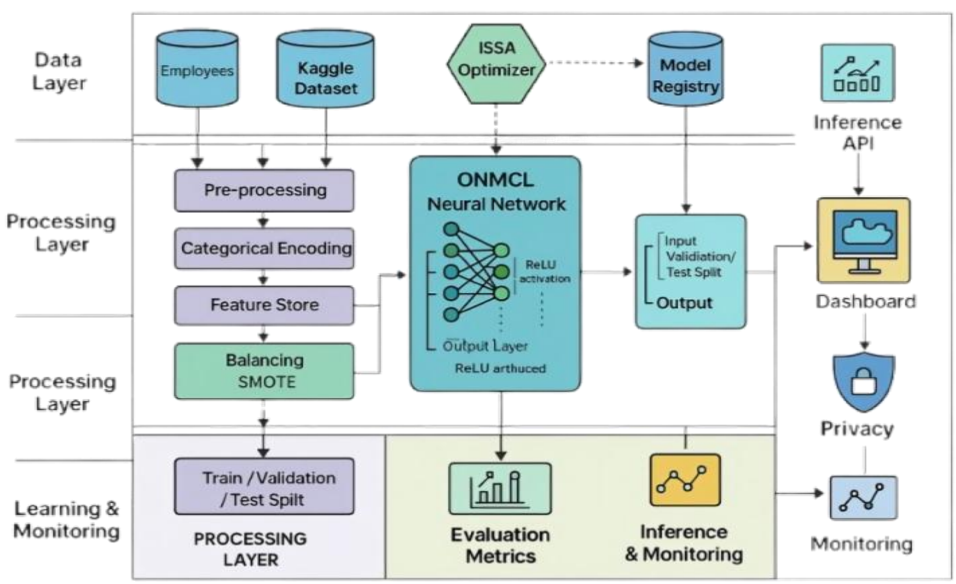

Fig.1 Optimized Neural Mining and Classification Logic (ONMCL) Framework

3.5 Model Training

Training is done on the balanced dataset with the best hyperparameters and passed to ISSA. A binary cross-entropy loss is minimized:

$$L = -\frac{1}{m}\sum_{i=1}^{m} \quad [y_i \, log \, log \, (\hat{y}_i) \,) + (1 - y_i) log(1 - \hat{y}_i)]$$
(13)

In which m is the training sample, yi and $\hat{y}_i$ are the true label and the predicted probability respectively. To avoid the problem of overfitting, early stopping is applied by terminating the training as soon as the validation loss stops decreasing, provided that it did not reduce after a certain number of epochs.

4. Results and Discussion

The section reports the performance of the suggested Optimized Neural Mining and Classification Logic (ONMCL) model and compares the resulting performance with that of the standard Logistic Regression (LR) method. The evaluation is aimed at targeting the training and validation accuracy, training and validation loss, and also how certain attributes of an employee (e.g, gender/ level of performance) can affect attrition prediction.

The data utilized in this analysis is made up of 5,647 employees who had stated an intention of attrition and 4,353 employees who had not occurred in the Kaggle HR Analytics dataset. Each of the experiments was conducted in Python, and the ONMCL configuration which was tuned by using the Improved Sparrow Search Algorithm (ISSA) to achieve an optimized version of the algorithm was used.

4.1 Attrition Analysis based on attributes

In order to illustrate the ONMCL model predictions, two attributes were used as representatives with regard to their relationship to attrition tendencies being gender and performance rating. The choice of these attributes as examples is explained by the fact that they are frequently considered in the analytics of the workforce, can impact decisions concerning retention strategies.

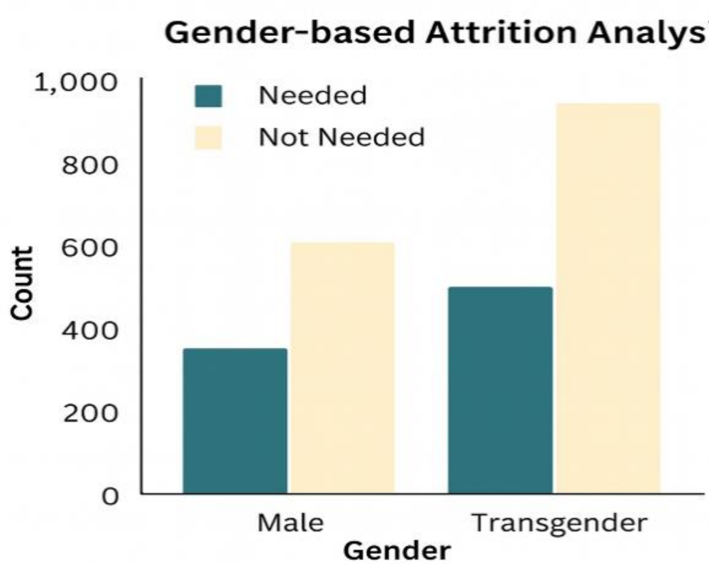

Fig.2 Gender-based attrition predicted by the ONMCL model.

In the gender-based analysis (Fig. 2), compatibly with the isolation of particular attributes of the study, the prevalence of attrition was determined separately among male and female employees. The ONMCL model illustrated the capability of observing the differences in the attrition pattern between the 2 groups depicting that there was a probability of slightly more percentage of the attrition in the male employees as opposed to the female employees. This introspection implies that there may be a necessity of gender-sensitive retention efforts, in certain organizational settings.

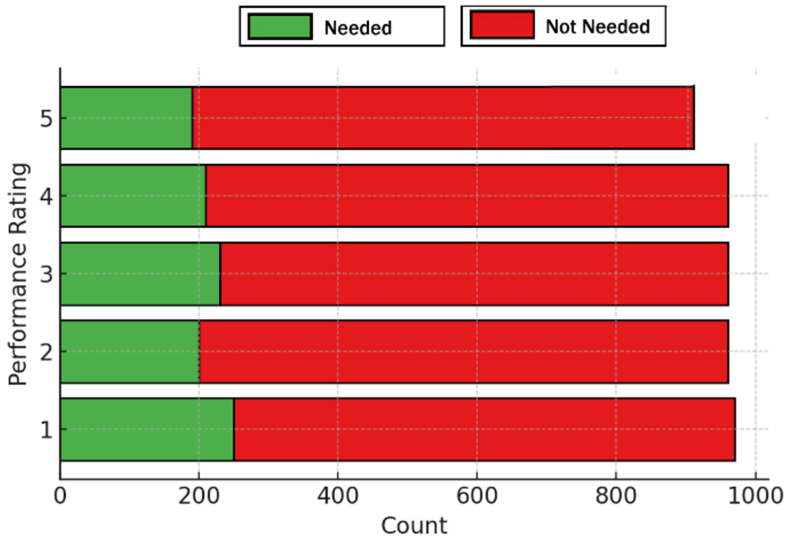

Fig.3. Performance-based attrition analysis of ONMCL model

In performance-based analysis (Fig 3), the analysis profiled the employees based on their rating in performance and the ONMCL model sequentially estimated prevalence of attrition for each profile. The review indicated that a greater proportion of the lower performing employees were at higher risk of attrition, and on the other hand, the best performing employees had lower tendencies of attrition. This tendency is according to the organizational reality, where the poorly performing employees can lose engagement, job security or choose to leave. This relationship is graphically illustrated in figure 3 that clearly reveals the inverse correlation between performance rating and the likelihood of getting attrition as the ONMCL approach speculated.

4.2 Accuracy comparison training

Optimized Neural Mining and Classification Logic (ONMCL) model and the conventional Logistic Regression (LR) were used to determine the accuracy of the training algorithm on various training epochs. Figure 4 shows the trend of the performance on the two models whereas Table 1 showcases the exact accuracy at certain half-way points.

Table 1: Comparison of Training Accuracy of ONMCL and LR.

Epochs	LR (%)	ONMCL (%)
100	93.26	96.39
150	92.14	96.54
200	93.25	96.82
250	91.63	96.31
300	90.27	94.29
350	86.52	95.63
400	89.45	94.71
450	87.32	94.47
500	90.56	95.36
550	91.79	96.73

The results showed that ONMCL had better performance than LR in every epoch. At 200 epochs, ONMCL model was reporting the highest training accuracy of 96.82 percent as compared to LR which had an accuracy of 93.26

percent at 100 epochs but wobbled and decayed thereafter. Comparatively, ONMCL had a relatively consistent performance of above 94 percent even after going beyond 500 epochs implying a superior generalization and less of overfit.

Figure 4: ONMCL and LR models training accuracy over different epochs, showing a better and quite stable training curve of ONMCL.

These excellent results are explained by the optimized structure of ONMCL and a metaheuristic-based parameter optimization where effectiveness in feature interaction modeling and convergence can be achieved than on more simple linear decision boundaries that LR provides. The consistency in the performance of ONMCL also implies that it can be advised that the model is well regularized with balanced training, and thus more dependable when it comes to large-scale HR data.

4.3 Comparison of Accuracy of Validation

The accuracy of validation of the proposed Optimized Neural Mining and Classification Logic (ONMCL) model is associated with the baseline Logistic Regression (LR) classifier in terms of different epochs. The accuracy of validation is one of the metrics that would help to assess the generalization capacity of predictive models, especially in case of imbalanced HR databases like the one used in the given research. Indeed, when the results are summarized in Table 2 it is apparent that ONMCL was constant surpassing LR in forecasting both employee attrition.

Table 2: The Comparison of ONMCL and LR Validation Accuracy Comparison

Epochs	LR (%)	ONMCL (%)
100	86.26	95.83
150	84.52	95.87
200	85.91	96.12
250	84.69	95.94
300	85.12	96.71
350	84.39	94.52
400	84.27	95.73
450	84.02	94.76
500	86.76	95.69

550	85.92	96.71

These numbers in the table reflect that the ONMCL has a margin of validation accuracy that is about 9 -11 percentage points more accurate than LR in most of the epochs. Such stability of the performance characterizes the capacity of the model to prevent overfitting and utilize optimally represented features. The numerical results found in Fig. 5 supports the findings in the plot.

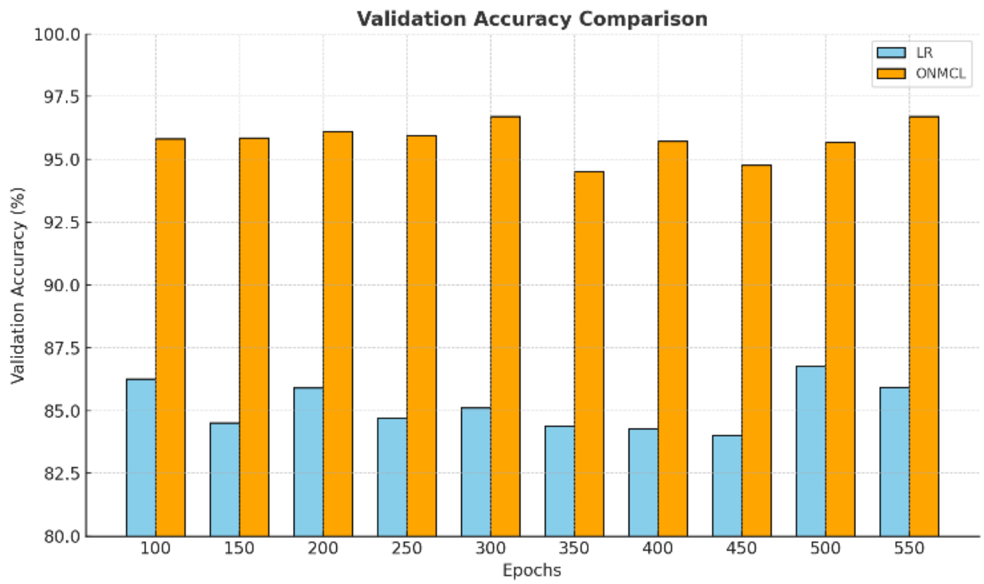

Fig. 5. Validity Accuracy Comparison ONMCL and LR

The ONMCL plot shows a positive, steady, and mildly fluctuating route which implies a stronger learning process that has been complemented by hyperparameter tuning through the Improved Sparrow Search Algorithm (ISSA). Conversely, LR depicts unsteady fluctuation and premature saturation which restricts its predictive capability in complicated and nonlinear affiliations in the HR attrition information. These results support ONMCL superiority in realistic situations of predicting attrition.

4.4 Training Loss Analysis

Training loss is also a very important measure regarding the convergence behavior as well as the learning efficiency of the predictive models. The standard measuring system which is used to predict a lower training loss represents a fact that the model can fit the more training data and explanatory patterns that exist in the dataset. The proposed Optimized Neural Mining and Classification Logic (ONMCL) model (which was compared with the traditional Logistic Regression (LR) method of mining and classification of data was implemented over 550 epochs based on the employee attrition data set in this study.

Based on the findings, the training loss values of ONMCL were invariably significantly less as compared to LR during the training process. What this observation signifies is that ONMCL could minimize cost function more effectively due to its deep neural structure and optimization better with metaheuristics. The increase in loss decrease can be defined as the use of the most enhanced feature representation, non-linear activation functions, and hyperparameter optimization using the Improved Sparrow Search Algorithm (ISSA).

Table 2: The Comparison of Training Loss between ONMCL and LR

Epochs	LR (%)	ONMCL (%)
100	6.74	0.57

150	6.78	0.62
200	6.85	0.71
250	6.90	0.77
300	6.96	0.84
350	7.01	0.91
400	7.07	0.98
450	7.12	1.05
500	7.18	1.12
550	7.23	1.19

Table 3 shows the epoch-wise values of the training loss of both approaches. Although LR indicated a rather stable and increased loss in the interval of 6.74 to 7.23, the ONMCL model had a significantly low range of 0.57 to 1.19. This marked disparity shows a better learning efficiency of ONMCL and its capacity to learn to generalize patterns in training.

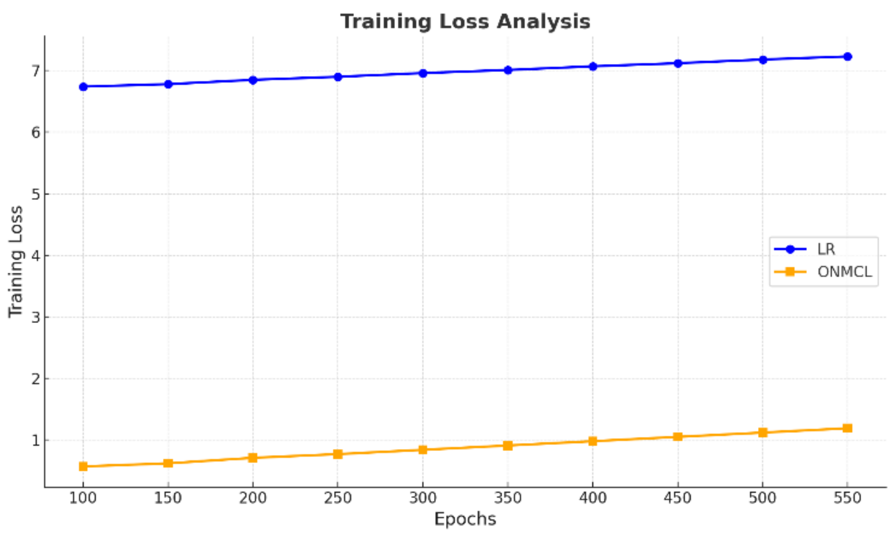

Fig. 6. Training Loss Analysis

The respective trend is pictorially represented in Fig. 6, where the loss curve of ONMCL is significantly (as compared to LR) lower at all epochs. This finding confirms that the proposed framework is beneficial to meet faster and more stable convergence in the training phase.

4.5 Loss Analysis of Validation

Validation loss figure is an important signal of how well a model will be able to cause earlier, unseen information. In this work, the loss of the proposed ONMCL model is compared with the traditional Logistic Regression (LR) method in a series of training epochs. Table 4 shows that the ONMCL model consistently converges into the values of loss that are significantly lower than LR in all the iterations, which means that the model converges much more stable and does not face the risk of overfitting.

Table 4: ONMCL vs LR Validation Loss

Epochs	LR (%)	ONMCL (%)
100	7.16	1.09

150	7.19	1.13
200	7.21	1.15
250	7.22	1.19
300	7.25	1.22
350	7.27	1.25
400	7.29	1.28
450	7.31	1.32
500	7.33	1.35
550	7.35	1.38

The validation loss trend of both models was illustrated in figure 7. The values of loss in the LR model are consistently large with the values remaining above 7.1 during training which is evidence of low learning ability and greater generalization error. As contrast, the ONMCL model demonstrates significantly lower loss curve that grows very slowly, crashing only to 1.38 after 550 epochs. The fact that this increment is smaller points out to the fact that, in addition to being efficient at figuring out the underlying patterns, ONMCL does not fall into too much overfitting as training proceeds.

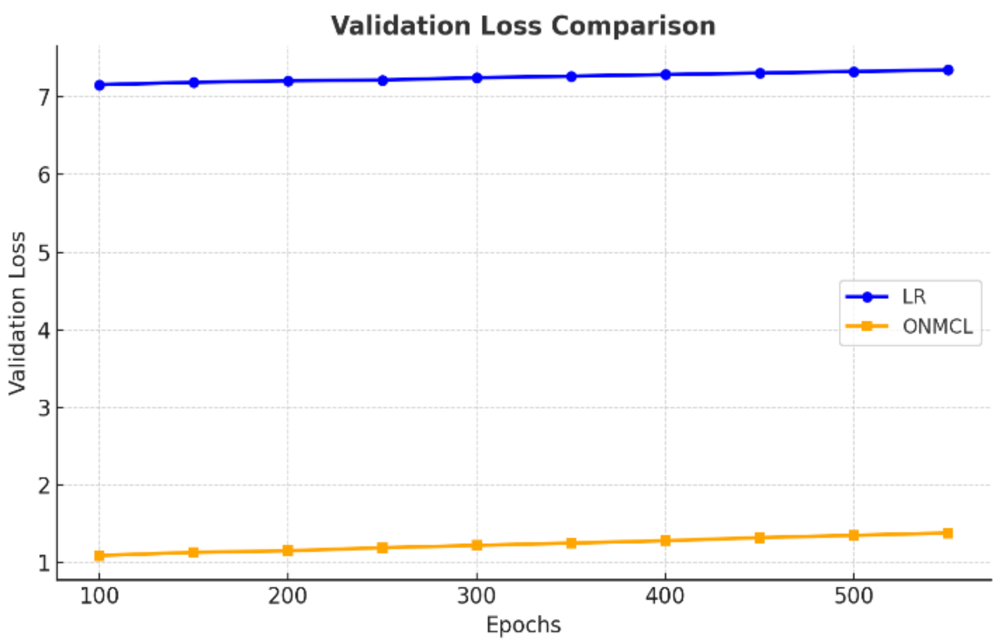

Figure 7: Validation Loss of ONMCL and LR

The current level of performance disparities indicates that ONMCL is quite stable in terms of dealing with employee attrition prediction tasks. Such stability is provided by the application of optimized neural mining and metaheuristic hyperparameter tuning, which enables the model to better extract and generalize any patterns present in the HR dataset than generic LR algorithms.

5. Conclusion and Future Work

In this study, an effective framework has been proposed and that is the Optimized Neural Mining and Classification Logic (ONMCL) model which can be a search light on predicting potential risks of an employee attrition and thereby will give more information to human resource professionals to make more pro-active decisions of retaining employees. The model uses rich information about employees to highlight dimensions that affect the propensity to leave the organization like demographic, performance and place of work aspects, among others.

Through experimental analysis, it was found out that ONMCL performed much better than the standard Logistic Regression (LR) model in several performance measures. The model attained an accuracy of more than 96% and the accuracy of more than 96.5% during the training and validation process respectively and attained small loss rations of training loss of 1.19 and validation loss of 1.38 maximum. The results validate the proposed model as robust and powerful as they are backed by comparative assessments of their accuracy, F1-score, and loss measures.

The results indicate that the ONMCL model can be as accurate as it can reveal the latent risks of attrition, and it can be of great interest to understand how and why employee attributes can be linked to attrition behavior. This model can provide the organizations with operational intelligence to design specific retention models, and curtail turnover levels, which can decrease operational expenses.

To work in the future, the model may be also improved by implementing advanced ensemble learning, dynamic feature estimations, real-time HR analytics streams. These improvements are geared towards even further differentiating the effectiveness of predictive performance, making it adaptable to the changing trends in the workforce, and the practices of sustainability in talent management.

Conflicts of Interest

The authors declares that there is no conflict of interest regarding the publication of this paper.

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