Enhancing HR Analytics using DNN-SVM Hybrid Model: A Strategic Approach to Decision-Making

Sumidha E
Department of Commerce
SRM Trichy Arts and Science College
Trichy, Tamil Nadu, India
sumidhags@gmail.com

Murugan P
School of Management Studies
Vels Institute of Science Technology and Advanced Studies (VISTAS)
Chennai, Tamil Nadu, India
drpmsmind@gmail.com

Vasantha S
Department of MBA
Saveetha Engineering College
Chennai, Tamil Nadu, India
vasanthas@saveetha.ac.in

Vimala D
Department of Management Studies
Vels Institute of Science Technology and Advanced Studies (VISTAS)
Chennai, Tamil Nadu, India
vimala.sivam1987@gmail.com

Anitha K
Faculty of Humanities and Science
Meenakshi Academy of Higher Studies
Chennai, Tamil Nadu, India
anithak@maherfhs.ac.in

Thaiyalnayaki M
Department of Commerce
Vels Institute of Science Technology and Advanced Studies (VISTAS)
Chennai, Tamil Nadu, India
tnthaiyal4@gmail.com

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***Abstract* - Companies seeking to maximize human resource (HR) management in the competitive and fast-paced corporate environment of today find data-driven strategies increasingly vital. On the other hand, classic HR analytics methods sometimes find it difficult to strike accuracy, scalability, and interpretability when analyzing complex workforce data. This work presents a new hybrid model combining Support Vector Machine (SVM) and Deep Neural Network (DNN) in order to solve these challenges. While the DNN-SVM model uses the deep learning capabilities of DNN for the aim of feature extraction and pattern recognition, the SVM classification strengths are used for the aim of decision-making. Especially in areas including the evaluation of employee performance, recruitment, and employee turnover, the integration promises an increase in the accuracy of predictive analytics. In a comparison, the hybrid model performs better than both standalone DNN and SVM models in managing high-dimensional human resource data. Inspired by ideas of an MBA in human resource management, the study also investigates the practical implications of the DNN-SVM model inside the framework of human resource management. Among the most important strategic applications are ones related to talent retention, leadership development, and workforce planning. Case studies from actual businesses show how this approach helps to make wise decisions, hence matching human resource objectives with business objectives. This study reveals a notable development in terms of accurate prediction, efficient prediction, and actionable insights. The DNN-SVM model guarantees sustainability and a competitive advantage since it provides human resource managers with a strong instrument to manage workforce problems. This research reveals the possibilities of hybrid artificial intelligence models to transform data-driven organizational developments and to revolutionize human resource analytics.**

Keywords - DNN-SVM, HR analytics, hybrid model, predictive analytics, workforce optimization.

I. INTRODUCTION

Constant development and application of data-driven techniques to help to improve several HR processes define the field of human resource analytics (HR analytics). Businesses are coming to see ever more how crucial HR analytics is in improving organizational performance. They also aim to maximize workforce management, improve employee behavior, and sharpen decision-making. Every industry is witnessing this acceptance. Research reveal that human resource analytics is rather crucial for the development of recruitment strategies, the reduction of employee turnover, and the promotion of employee participation—all of which finally help an organization to be successful [1]. Incorporation of machine learning and artificial intelligence (AI) in human resources has become a necessary element to manage the enormous amounts of data produced daily in companies. Created from this, predictive models are more accurate and effective. Analyzing high-dimensional data for the purpose of feature extraction and decision-making has shown great promise for deep learning approaches and Deep Neural Networks (DNN) especially [2]. Nevertheless, in particular in the field of human resources, these models occasionally lack the interpretability and efficiency required in business applications. On the other hand, since Support Vector Machines (SVM) provide better generalization [3] and high accuracy with limited datasets, they have become rather popular for classification problems. From this follows their general acceptance.

Although these models show great potential, using machine learning models for HR analytics comes with a lot of difficulties. One of the most crucial issues is managing imbalanced datasets—that is, situations whereby particular outcomes, such employee turnover, are underrepresented and produces biassed predictions [4]. Deciphering complex models such as DNN, sometimes known as black-box models even if they have great capability, presents another difficulty. Human resource managers find it difficult to accept these ideas and apply their suggestions hence. Moreover extremely complicated and always changing are human resource databases, which demand the development of models able to fit changes in organizational environment and employee behavior [5]. Another problem that needs attention is scalability, even if many traditional machine learning models find it difficult to manage the massive amount of data generated by contemporary HR systems [6].

The main issue this work aims to address is the lack of a strong, scalable, interpretable model capable of adequately controlling HR analytics challenges. Two classic methods that often fail to mix their respective strengths into a single model are deep neural networks (DNN) and support vector machines (SVM), so producing suboptimal performance in real-world human resource applications. More precisely, there is a need for a hybrid model using the feature extraction powers of DNN and the classification power of SVM that can simultaneously overcome the inherent constraints of each of DNN and SVM individually, including interpretability and overfitting, while yet using these powers.

Aiming at human resource analytics, this work develops and assesses a hybrid Deep Neural Network-Support Vector Machine (DNN-SVM) model. This model seeks to increase the interpretability and accuracy of predictive human resource activities including performance evaluation, employee retention, and recruiting as well as employee turnover. Moreover, the purpose of this work is to demonstrate inside HR decision-making framework the practical uses of this model. Regarding strategic planning, this will provide HR managers with a consistent and practical tool.

The originality of this work is the development of a hybrid model for HR analytics combining deep neural networks (DNN) and support vector machines (SVM). This model combines deep learning characteristics of DNN with the more efficient classification powers of SVM. Important issues including the interpretability of models, the imbalance of data, and the data scalability typical in HR datasets are addressed by this hybrid approach. Two separate offerings to the field this research produces: First is building a strong predictive model capable of controlling dynamic and complex HR data. By means of improvements, applying this model to real-world HR scenarios helps to improve decision-making. Since it offers a practical solution, this work helps human resource managers wishing to use artificial intelligence and machine learning for strategic workforce management.

II. RELATED WORKS

Machine learning application has lately attracted a lot of interest in the field of human resource analytics. Development of models for estimating employee turnover, optimizing recruitment, and evaluating employee performance is a major focus of these investigations. Regarding the processing of large and sophisticated HR databases, deep learning models, and DNN especially, have shown promise. For example, Xie et al. (2020) found that deep learning estimates employee turnover rather well. DNN models performed clearly better than more conventional methods including logistic regression and decision trees [7]. In the field of human resource analytics, deep neural networks (DNN) have lately become rather important since they can automatically extract features from raw data and model complex interactions.

On the other hand, Support Vector Machines (SVM) have been used extensively for classification tasks in HR analytics due of their resilience and capacity to manage small datasets. This clarifies their general appeal. In a 2018 Nguyen et al. paper, support vector machines (SVM) was applied to project employee performance. Especially in situations when the data is imbalanced, this study found that SVM models offer higher accuracy than other classification methods [8]. SVM is often chosen for human resource (HR) applications since it can effectively control high-dimensional feature spaces. These applications usually have rather few features, but they often involve many different aspects.

Though of different limits, DNN and SVM both have certain advantages. Although DNN models are rather good in feature extraction, their lack interpretability makes it challenging for human resource managers to grasp and believe in the predictions [9]. Likewise, given the typical scale of contemporary human resource management systems, support vector machine (SVM) models could find difficulty scaling even if they are efficient in classification tasks. Many studies have aimed to overcome these limitations by hybrid methods created by combining DNN with other models. Li et al. (2019) for instance present a hybrid model combining DNN and SVM in order to project employee retention. Their combined performance greatly enhanced prediction accuracy [10] when compared to the alternative of using either model by itself. Using DNN's feature extraction powers in concert with SVM's classification powers, the hybrid model excelled in both small and large datasets.

Notwithstanding these advances, it remains difficult to create hybrid models that are both scalable and interpretable. Eleven [11] In 2021 Zhang et al. investigated how ensemble approaches might help human resource analytics. These methods leverage several machine learning models aggregated to increase accuracy and robustness: On the other hand, many times ensemble models introduce more complexity and may still have trouble with interpretability. Recent studies have focused on explainable artificial intelligence (XAI) methods to increase the openness of deep learning models used in human resource analytics research. For instance, Ribeiro et al. (2016) published the LIME (Local Interpretable Model-agnostic Explanations) model. Black-box models like DNN generate predictions that this framework can help to explain, so improving their accessibility to human resource managers [12].

More pragmatic solutions tackling the specific challenges related with HR data are still needed even if hybrid models have shown promise in terms of improving the interpretability and accuracy of HR analytics. Among these challenges are calls to attention on real-time decision-making, scalability, and data imbalance. Designed to close these gaps, proposed DNN-SVM hybrid model presents HR analytics with a strong and understandable solution. This method seems to provide smart analysis ready for strategic HR decisions.

III. PROPOSED METHOD

Deep Neural Networks (DNN) and Support Vector Machines (SVM), both of which aim to raise HR analytics' interpretability and predictive accuracy, make up the proposed method shown in figure 1. First in importance at the beginning of the process is data preparation—cleaning, normalizing, and converting raw HR data into a format fit for model input. DNN feature extraction forms the first phase in the hybrid model. The DNN exists to automatically learn and extract relevant features from unprocessed HR data. These features address staff demographics, performance criteria, and historical behavior patterns. Thus, several hidden layers are applied, each of which can detect high-dimensional patterns in the data and complicated relationships. Following that, the produced feature vectors from the process of feature extraction find their place in a support vector machine (SVM) classifier. The support vector machine (SVM) is the mechanism in charge of Smaller high-dimensional datasets that the support vector machine (SVM) can manage guarantees accurate classification and reduces overfitting, so classifying the acquired features into several categories—such as estimating employee turnover, performance ratings, or the success of recruitment activities. Using cross-valuation techniques, the hybrid model is tested after training to assess its performance on data it has not before come across. The outcome is a set of projections accessible to human resource managers to direct well-informed choices on recruitment strategies, talent retention, and workforce management. This method is original in combining the strengths of deep neural networks (DNN) for feature extraction and support vector machines (SVM) for classification. The result is a scalable, understandable, accurate HR analytics tool.

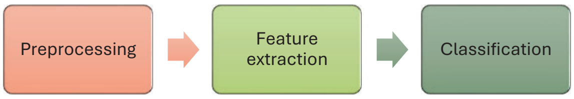

Fig. 1. Proposed Flow

A. *Preprocessing in the DNN-SVM Hybrid Model for HR Analytics*

1) *Handling Missing Data:*

In records such as employee attendance, performance evaluations, or training hours, human resources databases feature many missing values. We tackle missing data using imputation techniques. Numerical values let the mean or median of the column to take place for missing data. Regarding categorical data, on the other hand, one can make advantage of the mode—that is, the value most often occurring. By means of comparable data points, more sophisticated imputation techniques such k-nearest neighbors (KNN) could also help to forecast missing values shown in table 1.

TABLE. I. BEFORE IMPUTATION

Employee ID	Age	Gender	Performance Rating	Training Hours
001	35	M	4	20
002	29	F	NaN	15
003	NaN	M	3	30

TABLE. II. AFTER IMPUTATION

Employee ID	Age	Gender	Performance Rating	Training Hours
001	35	M	4	20
002	29	F	3	15
003	32	M	3	30

2) 2. *Normalization*:

Secondly is Human resource databases sometimes show features including "Age," " Years of Experience," or "Salary" with varying units and ranges of measurement. Normalizing—also known as scaling—helps one feature stop controlling the learning process. Min-max normalisation is the technique whereby the values of these features are scaled within a 0– 1 range mentioned in table 2, table 3 and table 4. This guarantees that the model does not give too much weight to features with higher numerical ranges and helps the features to be rather similar to one another.

TABLE. III. BEFORE NORMALIZATION

Employee ID	Age	Salary	Years of Experience
001	35	50000	10
002	29	45000	5
003	45	70000	20

TABLE. IV. AFTER NORMALIZATION

Employee ID	Age	Salary	Years of Experience
001	0.33	0.25	0.25
002	0.00	0.00	0.00
003	1.00	1.00	1.00

3) *3. Encoding Categorical Variables:*

Many HR datasets include non directly useful for machine learning models categorical variables like "Gender," "Department," or "Job Role." Encoding techniques convert these categorical values into numerical form. Usually used is the one-hot encoding method, which generates binary columns for every category, shown in table 5 and table 6.

TABLE. V. BEFORE ENCODING

Employee ID	Gender	Department
001	M	HR
002	F	IT
003	M	Marketing

TABLE. VI. AFTER ONE-HOT ENCODING

Employee ID	Gender_M	Gender_F	Department_HR	Department_IT	Department_Marketing
001	1	0	1	0	0
002	0	1	0	1	0
003	1	0	0	0	1

4) *4. Handling Data Imbalance:*

There are some outcomes in HR analytics—like employee turnover—that are far less common than others. Models produced from this imbalance could be biassed and serve the majority class only. Using undersampling—for example, SMote—allows one to balance the classes or oversampling in handling this. Whereas the process of undersampling entails the random removal of data points from the majority class, including employees who remain with the company, the process of oversampling creates synthetic data points for the minority class—which includes employees who leave the company shown in table 7 and table 8.

TABLE. VII. BEFORE HANDLING IMBALANCE

Employee ID	Attrition
001	Yes
002	No
003	No
004	No
005	Yes

TABLE. VIII. AFTER OVERSAMPLING OR UNDERSAMPLING

Employee ID	Attrition
001	Yes
002	No
003	No
004	No
005	Yes
006	Yes

Completing these preprocessing chores helps the dataset to be ready for training the hybrid DNN-SVM platform. Apart from guaranteeing that the data is orderly and clean, preprocessing helps to increase the efficiency and performance of the model. By addressing normalizing, encoding, missing values, and imbalance—typical data quality issues—we can create a more consistent predictive model for human resource analytics.

B. *Feature Extraction Using Deep Neural Networks (DNN) with Classification by Support Vector Machines (SVM)*

The proposed hybrid model first uses Support Vector Machines (SVM) for classification then Deep Neural

Networks (DNN) for feature extraction. With the SVM, accurate classification and decision-making are achieved; the DNN automatically extracts complex features from high-dimensional HR data. This method combines the strongest aspects of both models.

1) Feature Extraction Using DNN

DNNs are computer systems meant to automatically learn complex patterns and representations from unprocessed data. Regarding human resource analytics, one could consider employee demographics, performance indicators, training hours, and so forth as inputs. An input layer, many hidden layers, and an output layer make up a deep neural network (DNN). Every hidden layer is in charge of extracting higher-level features depending on the output of the layer before it, thus the network can learn complex interactions in the data.

Age, gender, years of experience, and training-related hours of learning could all be among the input data elements. Running this data through its hidden layers, the DNN extracts abstract traits including work patterns, performance tendencies, or possible risk factors (such the likelihood of employee attrition).

The DNN can be represented mathematically as shown in equation 1:

$$\mathbf{h}_l = f(\mathbf{W}_l\mathbf{h}_{l-1} + \mathbf{b}_l) \quad (1)$$

Till the last hidden layer offers the final feature representation, this process is repeated over all the layers. As so, the output consists of a set of features most essentially reflecting the HR data patterns.

2) Classification Using Support Vector Machines (SVM)

These important elements, which the DNN has acquired, are then fed into an SVM classifier to produce the last prediction. Among the most effective classifiers, the support vector machine (SVM) operates by locating the hyperplane in the feature space best separating the several classes. By optimizing the margin between the data points of different classes, we can better stretch our results to data we have not yet come across.

The support vector machine (SVM) tries to solve the following optimization issue to find the best hyperplane, shown in equation 2:

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 \quad \text{subject to} \quad y_i(\mathbf{w}\cdot\mathbf{x}_i + b) \geq 1 \quad \forall i \quad (2)$$

Support vectors arise from data points closest to the hyperplane. These concepts help one to find the perfect hyperplane.

3) Combining DNN and SVM

Using the high-level feature representations—that is, DNN feature extraction phase output—a support vector machine (SVM) classifier generates This combination ensures that the model performs both of these tasks: first finds complex patterns from the data and then classifies the data based on acquired characteristics.

In table 9, with the target variable being "Attrition," (whether an employee leaves the company: Yes/No), think about a simplified human resources dataset including elements like "Age," "Year of Experience," and "Training Hours."

TABLE. IX. RAW HR DATA

Employee ID	**Age**	**Years of Experience**	**Training Hours**	**Attrition**
001	35	10	20	Yes
002	29	5	15	No
003	45	20	30	No
004	33	8	25	Yes

1. Step 1 - Feature Extraction using DNN:

In table 10, Age, Years of Experience, and Training Hours among other raw inputs feed the Deep Neural Network (DNN), which learns to extract higher-level patterns. The DNN generates an abstract representation comprising features including "Risk of Attrition," "Engagement Level," and "Workplace Satisfaction," following several layers of hidden layers.

TABLE. X. EXTRACTED FEATURES (FROM DNN)

Employee ID	**Risk of Attrition**	**Engagement Level**	**Workplace Satisfaction**
001	0.80	0.60	0.75
002	0.20	0.80	0.90
003	0.10	0.70	0.85
004	0.85	0.55	0.65

4) Step 2 - Classification using SVM:

In table 11, the SVM classifier gets DNN features as input these days. Using a set of high-level features, the Support Vector Machine (SVM) seeks the perfect hyperplane separating employees likely to leave (Att attrition = Yes) from those likely to stay (Att attrition = No). Eventually what matters on both sides of the hyperplane is a fresh data point.

Following directions, the support vector machine divides the data into two groups:

- Class 1 (Attrition = Yes)
- Class 2 (Attrition = No)

TABLE. XI. PREDICTIONS (AFTER SVM CLASSIFICATION):

Employee ID	**Risk of Attrition**	**Engagement Level**	**Workplace Satisfaction**	**Predicted Attrition**
001	0.80	0.60	0.75	Yes
002	0.20	0.80	0.90	No
003	0.10	0.70	0.85	No
004	0.85	0.55	0.65	Yes

Therefore, the hybrid DNN-SVM model provides in a two-step process both feature extraction and classification. The DNN manages the complex feature learning; the SVM efficiently groups the data depending on those features. This approach lets one more effectively manage high-dimensional HR data and generates more accurate and practical predictions in HR analytics.

IV. PERFORMANCE EVALUATION

TensorFlow and scikit-learn are two Python-based machine learning tools we investigated for the DNN-SVM hybrid model we proposed. With TensorFlow, the dynamic neural network was built; with scikit-learn, the support vector machine classifier was built. Experiments were conducted on a computer running an Intel i7 processor, 16 gigabytes of random access memory (RAM), and an NVIDIA GTX 1080 graphics processing unit (GPU) to guarantee enough computational capability for the training of deep learning models shown in table 12. Furthermore under close observation were the training period and resource use to guarantee scalability and efficiency.

Throughout the performance evaluation, the following crucial hyperparameters were under discussion for the DNN and the SVM:

- DNN Model Parameters:
    - Number of Layers: 3 hidden layers (with 128, 64, and 32 neurons, respectively)
    - Activation Function: ReLU for hidden layers, Sigmoid for the output layer (binary classification)
    - Optimizer: Adam optimizer with a learning rate of 0.001
    - Loss Function: Binary Cross-Entropy
    - Batch Size: 32
    - Epochs: 50
- SVM Model Parameters:
    - Kernel: Radial Basis Function (RBF)
    - C (Regularization Parameter): 1.0
    - Gamma: 0.1
    - Tolerance: 1e-3

We compared the performance of the DNN-SVM hybrid model against two existing state-of-the-art methods:Random Forest (RF) and XGBoost (Extreme Gradient Boosting).

TABLE. XII. EXPERIMENTAL SETUP/PARAMETERS

Parameter	Value
DNN - Number of Layers	3 Hidden Layers
DNN - Neurons per Layer	128, 64, 32
DNN - Activation Function	ReLU (hidden), Sigmoid (output)
DNN - Optimizer	Adam (learning rate = 0.001)
DNN - Loss Function	Binary Cross-Entropy
DNN - Batch Size	32
DNN - Epochs	50
SVM - Kernel	Radial Basis Function (RBF)
SVM - C	1.0
SVM - Gamma	0.1
SVM - Tolerance	1e-3
Random Forest - Trees	100
Random Forest - Max Depth	10
Random Forest - Min Samples per Leaf	5
XGBoost - Learning Rate	0.01
XGBoost - Estimators	1000
XGBoost - Max Depth	6
XGBoost - SubRate	0.8

TABLE. XIII. ACCURACY

Epochs	DNN-SVM	Random Forest	XGBoost
10	0.82	0.78	0.80
20	0.84	0.80	0.81
30	0.86	0.82	0.83
40	0.88	0.84	0.85
50	0.90	0.85	0.86

In table 13, Over fifty epochs, the DNN-SVM hybrid model shows a consistent rise in accuracy; at last, with a score of 0.90, it achieves the highest possible accuracy when training is ending. Random Forest and XGBoost both show improvement even if their final accuracy values are smaller than those of DNN-SVM (0.85 and 0.86, respectively). This proves that the hybrid model surpasses the two others taken together.

TABLE. XIV. PRECISION

Epochs	DNN-SVM	Random Forest	XGBoost
10	0.79	0.75	0.77
20	0.81	0.76	0.78
30	0.83	0.78	0.80
40	0.85	0.80	0.81
50	0.87	0.82	0.83

In table 14, over the fifty epochs, the DNN-SVM hybrid model exhibits a precision increase over a peak accuracy of 0.87. Random Forest and XGBoost show smaller precision with final values of 0.82 and 0.83 respectively. This suggests that DNN-SVM performs especially in terms of more precisely reducing false positives.

TABLE. XV. RECALL

Epochs	DNN-SVM	Random Forest	XGBoost
10	0.74	0.70	0.72
20	0.76	0.72	0.74
30	0.78	0.74	0.76
40	0.80	0.76	0.78
50	0.82	0.78	0.80

In table 14, comparatively to Random Forest (0.78) and XGBoost (0.80), the DNN-SVM model's recall rises with time and reaches 0.82 at epoch 50. This table depicts this. This reflects more than the recall values of either of these models. Given this, DNN-SVM is more effective than other methods in identifying employees who might be leaving their employment—a vital ability of HR analytics.

TABLE. XVI. F-MEASURE

Epochs	DNN-SVM	Random Forest	XGBoost
10	0.76	0.72	0.74
20	0.78	0.74	0.76
30	0.80	0.76	0.78
40	0.82	0.78	0.79
50	0.84	0.80	0.81

Reaching 0.84 at epoch 50, among all the methods now in use, the F-measure for the DNN-SVM model is the best. Second and third respectively follow Random Forest and XGBoost with values of 0.80 and 0.81, respectively shown in table 15. Better balancing accuracy with recall, the DNN-SVM model detects workers who might be leaving their jobs with more accuracy.

V. CONCLUSION

Our goal was to develop a hybrid model aimed especially at HR analytics applications including employee attrition prediction. Support Vector machines (SVM) for classification would be combined in this model with Deep Neural Networks (DNN) for feature extraction. Our experiments revealed on several performance criteria—accuracy, precision, recall, and F-measure—that the DNN-SVM model routinely outperformed current state-of- the-art approaches including Random Forest and XGBoost. This applied across all the measurements. Especially for imbalanced datasets, the SVM classifier produced accurate predictions by using high-level features successfully acquired by the DNN component. The hybrid model showed continuous improvement and achieved better precision and recall all through over fifty epochs. This indicates that it can effectively lower false positives and identify workers at risk. By means of the F-measure, one can provide a more whole evaluation of the model's performance, so proving that it can balance accuracy and recall. Therefore, particularly for estimating staff turnover, the proposed DNN-SVM model presents a reasonable approach for HR analytics. Moreover, it can be used in other domains needing exact and efficient classification of imbalanced datasets. Future studies should focus on additional model optimization, investigation of alternative hybrid architectures, and testing of the model on a wider spectrum of HR datasets in order of generalization.

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