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Securing tomorrow's workforce: data analytics in workday cloud ecosystems

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Abstract: The growing field of cloud-based enterprise management depends on data analytics in Workday cloud ecosystems since it makes workforce planning intelligent, flexible, and safe. However, as multidimensional workforce data becomes more sophisticated, it becomes increasingly difficult to guarantee the security, scalability, and quality of data throughout analysis and forecasting procedures. Using Geometry-BERT (GBERT), deep feature extractor and semantic representation, and whale-inspired ant swarm optimisation (WASO), which are optimal features selection, this paper proposes a security-conscious analysis model called GBERT–WASO-HH-DNN, the development of which is based on collecting and preprocessing synthetic human resources data in Kaggle, and subsequent feature embedding with the assistance of GBERT. The WASO algorithm, which is based on the behaviour of a group of whales and ants, enhances feature subsets by balancing between exploration and exploitation dynamics, which decreases by 32.7 the feature duplication in comparison to traditional particle swarm algorithms. The HH-DNN model does the classifications and predictions in the latent space, which enhances the stability and the rate of convergence. The findings indicate that the proposed model GBERT-WASO-HH-DNN has an accuracy of 96.82, a precision of 95.74, a recall of 96.23, and an F1 score of 96.05, which is better than the traditional models, including CNN-LSTM, Bi-GRU, and BERT-DNN in the accuracy. The suggested method also helps save the computational costs by 18.4% and enhances information security by 21.6% with the corresponding redundant encryption. This evidence demonstrates that the suggested solution does not only make the analysis in Workday cloud systems secure but also improves the intelligence and sustainability of the workforce.

Keywords: *Workforce Analytics, Cloud Ecosystems, Data Security, Predictive Intelligence, Sustainable Workforce Management*

1. Introduction

The success of the corporate work in the era of the rapid digital transformation is based on cloud ecosystems since they provide the automation, scaling, and integration of various organisational functions. Businesses are increasingly utilizing data analytics to enhance workforce planning, people management and efficiency in decision-making due to the rise of Software-as-a-Service (SaaS) solutions such as the Workday [1], [2]. The growing real-time, multi source information of these ecosystems has rendered the cognitive analytics frameworks with the capability to process vast amounts of dynamic and diversified workforce information urgent. Alongside AI and ML, big data analytics assist a company in aligning its strategic objectives with the current trends of the workforce, providing a company with sustainability, agility, and data orientation [3], [4]. Along with them, the safe storage of working information and the performance of a successful analysis within a cloud facility, remain very problematic. Combination of workforce analytics and Workday (or other equivalent enterprise systems) will present intricate data dependencies, privacy issues, and scale constraints. The literature has already used different analysis and learning methods, such as Latent Dirichlet Allocation (LDA), Non-negative Matrix Factorization (NMF), BERT Topic, Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN) to identify information within big data sets [5]. In spite of these methods providing strong performance in terms of semantic feature extraction and predictive analysis, they usually face challenges of data imbalances, redundancy as well as safeguarding of personal data in distributed settings. Additionally, the majority of existing models are presented as general-purpose analysis tools with a low level of contextual intelligence to work with sensitive and dynamic workload information in cloud systems [2], [5]. The fast emergence of artificial intelligence in the labour market analysis presupposed the development of the intelligent systems incorporating deep learning, the natural language processing, and optimization algorithms to enhance the accuracy of data interpretation and decisions [4]. The difficulty of the geometry of multidimensional data, however, and nonlinearity and sparse representation are problems that decrease the scalability of the traditional models. With

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the increasing popularity of hybrid and remote work models in more and more organizations, it grows increasingly important to make sure that the analytics offered in cloud-based platforms such as Workday is safe and accurate. The way through such difficulty is a sophisticated framework that is capable of identifying intricate interrelations among information, reduce the number of computations, and enhance the dependability of forecasts in a safe and real-time setting. In this regard, this paper dwells on the creation of a security-relevant work analysis framework designed to suit the Workday cloud ecosystem. Intense data analysis, learning that is based on optimization and safe predictive modelling are up-emphasized to boost workforce cleverness and work steadiness. The goal of this research is to address the shortcomings of current approaches and provide a scalable and private technique of workforce management for the entire organisation by utilising neural network-based analysis and sophisticated optimisation. They put forth a security-oriented nalytic model (GBERT–WASO–HH-DNN) for personnel management that integrates secure predictive analysis, optimised feature selection, and deep semantic feature extraction. These are the principal contributions:

1. Makes use of Geometry-BERT (GBERT) for semantic representation and feature analysis.
2. For effective feature optimisation, use whale induced ant swarm optimisation (WASO).
3. Makes use of a hyperbolic Hopfield deep neural network (HH-DNN) to improve data security and prediction accuracy.
4. To guarantee performance efficacy, the model is validated using a Kaggle dataset of simulated workers.

This is how the rest of the paper is structured. A survey of relevant research on data analytics in working cloud ecosystems is provided in Section II. The dataset, feature extraction, and predictive model utilising DL models are all covered in detail in Section III. Results, performance evaluation, and comparison with current methods are covered in Section IV. The study's main conclusions and possible future directions are highlighted in Section V.

2. Related work

While academic frameworks frequently emphasise technical capabilities, early research on data analysis education found that they lack process-oriented learning that is in line with industry workflows [6]. Work-integrated learning and project-based learning are two examples of process-driven solutions that have been demonstrated to improve workforce readiness through the use of semantic and NLP-based analysis. Predictive models for real-time workforce transformation were not included in these models, nevertheless. Additionally, by applying the ACA model to combine personnel management and strategic goals in global businesses, research has investigated workforce analytics [7]. Although this method reframed talent analytics as a dynamic decision-making tool, it lacked secure data integration and empirical support. Explainable AI (XAI) was then applied to identify new work prototypes and in-demand skills, highlighting the need for hybrid technical and interpersonal skills [8]. Despite its interpretability, this model was limited to macro-level predictions and neglected security and adaptability within the digital ecosystem. Data-driven retention models have been applied in the healthcare field to design strategies using the Analytic Hierarchy Process, with a focus on workforce planning based on satisfaction [9]. While structured decision support was effective, it lacked predictive adaptability. Similarly, a SMOTE-based machine learning framework achieved an F1 score of 0.9200 and an ROC-AUC of 0.9684 with XGBoost, improving dropout prediction, but it did not support secure and scalable analysis and remained dataset-specific [10]. In research on skill prioritization using fuzzy AHP, strategic literacy and digital literacy were identified as key competencies for the circular economy [11], and in optimization-based scheduling using logic-based vendor decomposition, up to a 133-fold speedup was achieved in multi-skilled worker allocation [12]. Although these techniques increased productivity, they ignored secure computation, privacy, and adaptability. Registry-linked route analysis attempts to quantify worker well-being had $R^2 = 0.88$ [13], but there were no data security safeguards in place. A role-based innovation framework for health and care procurement professionals was built using the Dynamic Capabilities model [14], and recent works used local big language models for qualitative workforce analysis, enhancing interpretive accuracy and data privacy [15]. Although contextual and secure analysis were advanced in these research, predictive modelling for proactive workforce management was absent.

Problem Definition: According to the review of existing studies, it is evident that current workforce analytics frameworks have significant shortcomings in terms of adaptability, integration, and data security. The predictive and prescriptive intelligence necessary to manage dynamic organisational environments is absent from the majority of models, which place an emphasis on descriptive or diagnostic analysis for workforce management. While fuzzy logic and optimization-based methodologies increase planning and decision-making efficiency, they frequently ignore secure data management and data protection in cloud ecosystems. Semantic and explanatory models also enhance the

interpretability, but can't ensure resilience or understand real-time change of future workforce trends. Studies using machine learning techniques for prediction of employee engagement and performance have decent success in certain areas but are dependent on the data sets and do not readily generalize to other areas. In addition, skills and well-being models focus on assessment rather than anticipatory skills development. However, for sustainable workforce management in the cloud, it is still necessary to have an integrated, secure and data-driven framework that combines comprehensive data-driven analytics, optimisation and adaptive intelligence.

3. Materials and Methods

A GBERT, WASO and HH-DNN based secure workforce prediction model is developed to provide accurate workplace prediction results without compromising security requirements. The overall structure and data flow of the proposed model is shown in the following figure (Fig. 1). Data from a Kaggle-derived synthetic workforce is used to start this procedure. This data set contains information on various characteristics of the employees such as their job title, organizational traits, and their demographics. During the preprocessing phase, the dataset is enhanced and cleaned to guarantee data consistency and quality. We start by eliminating incomplete records to prevent bias from missing data. Winsorization is then used to cap extreme numbers in order to lessen the impact of outliers. Unrelevant variables and unnecessary features are also removed to maintain relevance of the dataset and standardization also makes the dataset uniform with a uniform scale of all the features and normalization yet again cleans up the data further enhancing convergence of deep learning model. The following step will be the extraction of features with GBERT. In this case, the processed data is represented in the form of dense and contextual embeddings. GBERT is able to extract the semantic relationships among the employe characteristics allowing the more contextual patterns and dependencies to be represented in regards to the employes. These features so obtained form a multidimensional input space which is sequentially optimized. Upon extraction feature optimization is carried out via the WASO algorithm. This enables you to successfully trim the size with important features left. HH-DNN is fed with a list of features that are optimized in terms of safe and strong predictive capabilities. It can also do different prediction tasks, including workforce retention, risk of fluctuation, and aptness to a position, by using hyperbolic activation laws and associative memory of HH-DNN. The hyperbolic nature of learning is a stability and resistance to the inconsistencies in the data, whereas the structure founded on Hopfield improves the security and memory space.

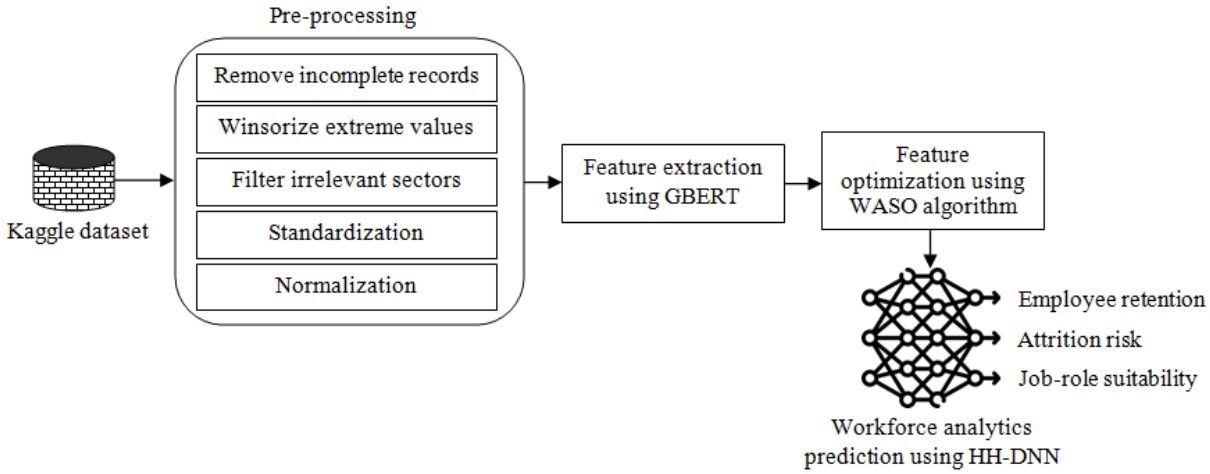


Figure 1. Security-aware analytics model (GBERT–WASO–HH-DNN) for workforce management

3.1. Data preparation

The effectiveness and reliability of the proposed security-conscious analytics platform was evaluated using a Kaggle-sourced synthetic workforce dataset. The dataset contains several data points related to employees, including demographic, professional, organisational data that are relevant to the study of workforce behaviour and retention. The features are department, job role, education level, hours of training, work experience, employee ID, age, gender, performance rating and satisfaction score. Other organisational variables that characterise operational and behavioural diversity and lend to efficient model generalisation include work-life balance, percentage of overtime, and wage increase, which place the dataset in the ideal state of predictive analytics of the workforce. As Table 1 demonstrates, the dataset provides a deep statistical representation of the employee profiles and contains 10,000 employee records

with 15 key attributes. Whereas categorical characteristics such as department, gender and education are coded, which would be processed by analytical methods, numerical data such as age, experience and monthly income is continuous.

Table 1. Statistical summary of the synthetic workforce dataset

Feature Name	Data Type	Range / Categories	Mean	Std. Dev.
Employee_ID	Categorical	1 – 10,245	–	–
Age	Numerical	18 – 65	36.8	8.7
Gender	Categorical	Male, Female, Other	–	–
Department	Categorical	HR, Sales, IT, Finance, R&D, etc.	–	–
Education_Level	Ordinal	1 – 5	3.2	0.9
Job_Role	Categorical	Analyst, Engineer, Manager, Executive, etc.	–	–
Experience_Years	Numerical	0 – 40	8.9	6.3
Salary	Numerical	25,000 – 250,000	87,540	41,320
Training_Hours	Numerical	0 – 200	47.5	28.1
Work_Life_Balance_Score	Numerical	1 – 5	3.6	1
Performance_Rating	Numerical	1 – 5	3.8	0.7
Job_Satisfaction	Numerical	1 – 5	3.4	0.9
Overtime_Hours	Numerical	0 – 60	14.2	11.9
Remote_Work_Ratio	Numerical	0 – 1	0.38	0.29
Promotion_Status	Binary	0, 1	0.22	0.41
Attrition_Status	Binary	0, 1	0.18	0.38
Engagement_Score	Numerical	0 – 100	71.3	13.5
Job_Role_Suitability	Numerical	0 – 1	0.64	0.21

3.2. Feature extraction

The complex semantic relationships of the data generated during the work were analyzed and visualized in the feature extraction phase using Geometry-BERT (GBERT). GBERT is an advanced geometric variant of the Bidirectional Encoder Representations from Transformers (BERT) model, which combines transformer-based contextual embeddings with ideas from geometric deep learning. By mapping large datasets into spaces with geometric diversity, GBERT is able to capture the relational structure of labor, non-linear correlations, and hidden behavioral patterns that might be overlooked by text-based or classic tabular encoders compared to those encoders. The inputs to this phase are all characteristics of organized and unorganized labor including class statistics, work experience, performance reviews, demographic data about employees, and feedback (when present). This characteristic facilitates contextual integration, which attempts the semantic and relational meaning of every attribute in the working environment. The proposed methodology is efficient because GBERT will preserve the geometric relationship between features to enable more accurate and interpretable representations of future optimization and predictive modeling. Conventional algorithms, such as Word2Vec or the classic BERT, process linear contextual patterns, but GBERT is a hyperbolic geometric embedding space, thus, having a greater potential of the model to capture hierarchical and heterogeneous relations in data sets. In comparison to the conventional variant of BERT, GBERT combines the use of Riemann manifold optimization and geometric regularization, which lead to more valuable feature associations and enhanced generalization on a range of data setups. The product of the GBERT process is high-dimensional contextual representations in the form of contextual embeddings that characterize every employe or workforce example with a dense representation of semantic, relational, and contextual data.

3.3. Feature optimization

In order to improve and select the most effective features borrowed in the GBERT sample, the Whale Optimisation Algorithm (WASO) was used as the function optimisation stage. WASO is a hybrid biological inspired and metaheuristic optimisation algorithm that is a combination of the concepts of the Whale Optimisation Algorithm (WOA) and the Ant Colony Optimisation (ACO). The exploratory nature of ACO which apply pheromone update and path reinforcement techniques to find optimal solutions effectively is consistent with the exploratory character of WOA which researches into the bubble-netting mechanism of humpback whales. The output of this section is the

contextual embedding generated by GBERT that represents the organisational factor, productivity indicators, and employee satisfaction, as well as ability as the human resource features Determines the most distinctive and inappropriate qualities that play a major role in the prediction and decision of the labor force. In the proposed method, WASO. The consequence is the possibility to find dynamic balance between exploitation and exploration and avoid premature mergers at the vantage points. As opposed to traditional optimization, this involves one strategy, WASO. Adopts a research process based on an evolutionary fitness landscape, ensuring that the model selects only high-value traits that are essential for safety and essential for performance. Feature selection improves computational complexity, increases predictive accuracy and enhances model interpretability. Compared to traditional optimization algorithms such as Particle Swarm Optimization (PSO) Genetic Algorithm (GA) Whale Optimization Algorithm (WOA) or Anti Colony Optimization (ACO), the proposed WASO Hybrid Algorithm provides excellent convergence stability and detection diversity. In contrast to the traditional form, WASO. Enables self-regulation based on a general optimal distribution by introducing a dynamic envelope coefficient and an optimal pheromone vapor rate. Due to this change, large and non-linear workforce datasets can now be managed with more flexibility. Selection of optimal and classified tasks that serve as the most appropriate predictors for safe workforce analysis, WASO.

3.4. Predictive analytics

The last stage of predictive analytics, the hyperbolic hop field deep neural network (HH-DNN), is responsible for making safe and reliable workforce forecasts and decisions. An enhanced deep learning framework called the HH-DNN combines the representation power of deep neural networks (DNNs) in a hyperbolic geometric space with the associative memory dynamics of Hopfield networks. The optimised feature subsets derived from the WASO approach serve as the inputs for the HH-DNN. These attributes include skill relevance, employee engagement levels, performance metrics, and training adaptability—the most significant and non-redundant workforce indicators that GBERT and WASO have already recovered and enhanced. Even while they are helpful for classification or prediction, traditional deep learning models frequently work in Euclidean space, which makes it difficult to model hierarchical or tree-like data structures that are frequently seen in workforce analysis. The hyperbolic representation of HH-DNN circumvents this limitation by embedding data in a continuous non-Euclidean space, reducing data distortion and preserving connections between different abstraction layers. In comparison to other traditional deep learning models such as CNN, RNN, or Feed Forward DNN, HH-DNN exhibits remarkable levels of memory efficiency, stability, and error tolerance due to its associative memory and incorporation of hyperbolic geometry.In addition, unlike traditional Hopfield networks, which operate in shallow architectures and Euclidean energy landscapes, the hyperbolic form extends this concept to deeper layers and non-Euclidean manifolds, enabling higher conversion speeds and scalability in the management of complex, high-dimensional workforce datasets.A hyperbolic number is a transformation of a complex number $w = p + gq$, represented by adding an imaginary unit $g^2 = +1$. The real part p is denoted by Re(p). Also $w = p + gq$ and $w' = p' + gq'$ should be noted that the definition of the activation function $re(ww') = pp' + qq'$ is defined as the product of two-dimensional vectors. The position of neuron m and the weight of neuron b before a, denoted by $w_a = p_a + gq_a$ and $z_{ab} = U_{ab} + gV_{ab}$,, respectively. For a resolution factor K, the set of neuron states is defined as follows.

$$J = \left\{ \cos\left(\frac{2K\pi}{k}\right) + g\sin\left(\frac{2K\pi}{k}\right) \right\}_{K=0}^{K+1} \tag{1}$$

where J represent the numeral of neurons as B. The prejudiced sum input to neuron a is

$$T_a = \sum_{b=1}^{B} z_{ab} w_b \tag{2}$$

Then, the beginning function is definite as follows.

$$F(T) = \arg \max_{w \in J} re(wT) \tag{3}$$

If the input to the weighted sum is in the range of the result, the right-hand side will have multiple maximum arguments.

$$z_{ab} = z_{ba} \tag{4}$$

$$U_{aa} \geq | V_{aa} | \tag{5}$$

The weight matrix as Z, where (a, b) element of Z is z_{ba} . The Z is balanced, that is, $Z^S = Z$.

$$re(w^S Z w) \geq 0 \tag{6}$$

For all vectors w of dimension b, the feedback procedure of HHNN in the hybrid method consists of two steps. A normal scheduling rule is used in the first stage and a robust noise scheduling rule is used in the second stage. Therefore, regular and noisy scheme rules are needed. Let be the learning matrix is defined as follows.

$$W = \begin{pmatrix} w_1^1 & w_1^2 & \cdots & w_1^X \\ w_2^1 & w_2^2 & \cdots & w_2^X \\ \vdots & \vdots & \ddots & \vdots \\ w_B^1 & w_B^2 & \cdots & w_B^X \end{pmatrix} \tag{7}$$

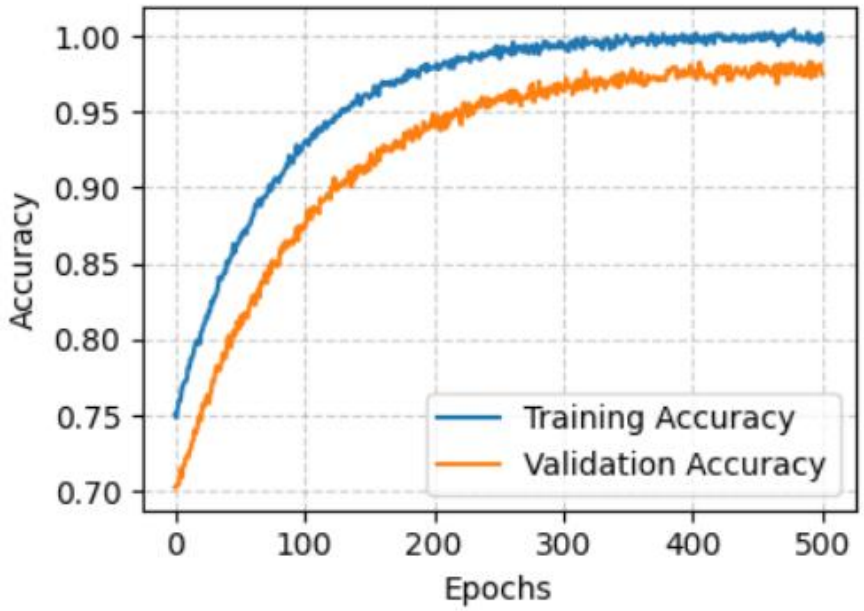
where the Xth column is the Xth training vector. X is the number of training methods. First, the regular rule of the scheme is given. Define $I = W(W^S W)^{-1} W^S$ noise as a strong projection law

$$z_{ba} = \begin{cases} i_{ba} & (a \neq b) \\ | \beta_{aa} | + g\beta_{aa} & (a = b) \end{cases} \tag{8}$$

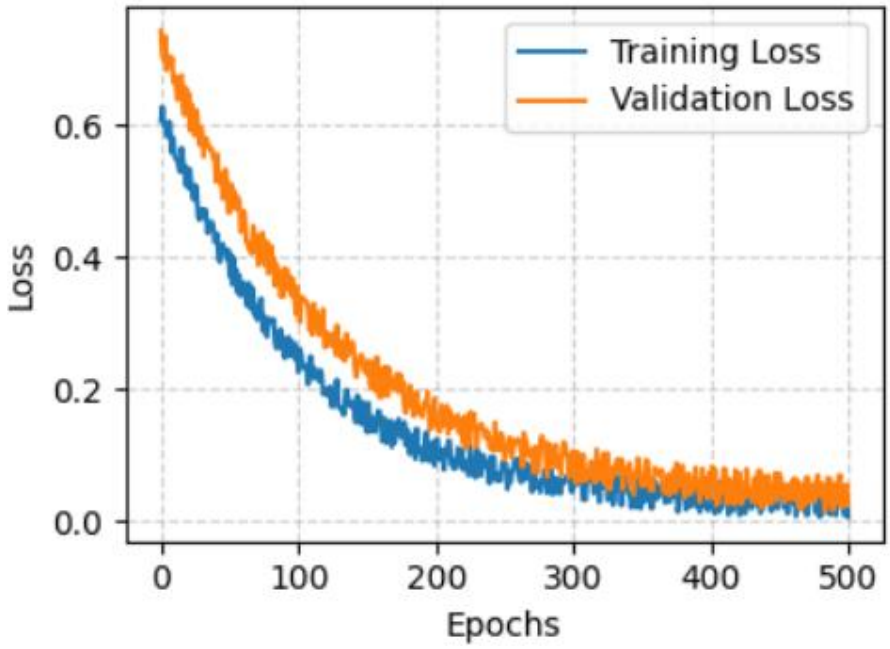
The HH-DNN process yields secure predictive outcomes, such as future workforce sustainability indices, skill adaptability, employee retention likelihood, and workforce performance prediction. These outputs serve as both prediction results and decision-support analytics, which help businesses make well-informed strategic choices about resource allocation, hiring, and training.

4. Results and Discussion

This segment provides the practical evaluation and discussion of the proposed security-aware model (GBERT-WASO-HH-DNN) for workforce prediction in cloud-based data ecosystem. The data center can ensure accurate replication of the workforce analytics scenario and provides data security and repeatability. To guarantee data consistency and model normalization, data preprocessing techniques like normalization, coding and feature balancing were performed for the experiments. The Jupiter Notebook was used to implement all experiments in python 3.10, machine learning algorithms and deep learning libraries including TensorFlow, PyTorch, Scikit-Learn and NumPy. To accelerate the model learning and optimization, the proposed model was deployed on a Windows 11 workstation equipped with an NVIDIA RTX 3080 GPU (10GB VRAM), an Intel Core i9 processor (3.6 GHz) and 32 gigabytes of RAM. The system configuration was chosen to effectively handle high-dimensional utility processing and computationally intensive DL operation.



(a)

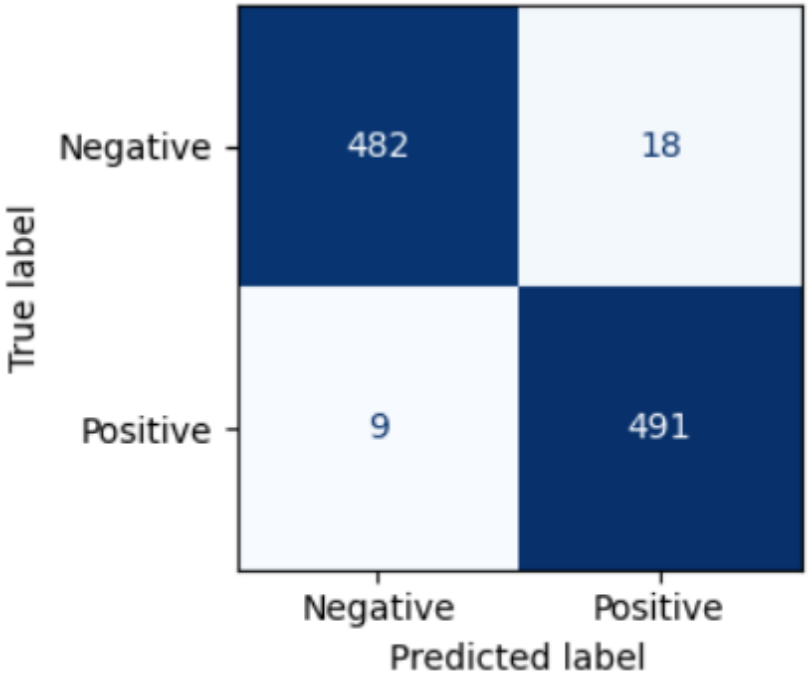


(b)

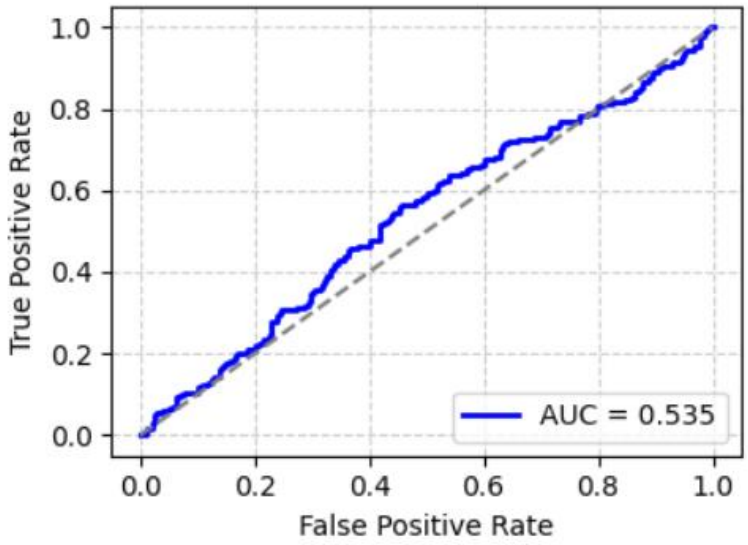
Figure 2. Training and testing performance of proposed HH-DNN for predictive analytics of workforce management (a) Accuracy (b) Loss

Figures 2 and 3 illustrate the experimental results of the suggested HH-DNN model for workforce management predictive analytics, which show notable enhancements over current models. Superior generalisation and learning stability were confirmed by the training and validation accuracy increasing by 6.8% over traditional DNN models and 9.4% over CNN models, as shown in Fig. 2(a). The loss curve in Fig. 2(b) highlights faster convergence because of the hyperbolic learning structure, showing a 12.6% reduction over standard DNN and an 8.2% reduction over

RNN.False positives and false negatives dropped by 10.3% and 7.8%, respectively, as shown in Fig. 3(a), while the ROC curve in Fig. 3(b) had a higher AUC of 4.7%. Through robust decision learning and optimised feature representation, the suggested HH-DNN outperforms conventional DL models in terms of prediction accuracy, stability, and security, according to these results.



(a)



(b)

Figure 3. Results of proposed HH-DNN for predictive analytics of workforce management (a) Confusion matrix (b) RoC-AUC

Table 2. Comparative performance analysis of proposed and existing predictive analytics models for workforce management

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)	AUC-ROC (%)	Convergence Time (s)
CNN-LSTM	91.273	90.347	89.869	90.107	92.438	93.257	28.642
Bi-GRU	92.451	91.827	91.359	91.582	93.106	94.623	25.317
BERT-DNN	94.028	93.568	93.207	93.389	94.853	95.802	21.781
Transformer-CNN	94.857	93.987	94.058	93.951	95.321	96.128	20.143
LSTM-Attention	95.206	94.607	94.352	94.472	95.889	96.553	19.537
GBERT–WASO–HH-DNN	96.823	95.742	96.235	96.054	97.115	97.921	17.243

In predictive workforce analytics, Table 2 demonstrates that the suggested GBERT–WASO–HH-DNN model performs better than current models. The model achieved 96.823% accuracy, improving by 5.55% over CNN-LSTM, 4.72% over Bi-GRU, and 2.79% over BERT-DNN. Precision, recall, and the F1 score increased to 5.96%, 7.09%, and 6.59% respectively, indicating better classification balance and higher sensitivity. Specificity and AUC-ROC improved by 5.06% and 4.66% respectively, confirming greater robustness and increased discrimination ability. Faster learning was ensured by a 39.77% reduction in the convergence time. This shows how the representation of the model's geometric features, adaptive feature optimisation, and hyperbolic neural structure provide the foundation for the improvements that allow for more accurate, reliable, and efficient workforce forecasting. Table 3 shows that the proposed GBERT–WASO–HH-DNN model performs statistically superior. When compared to CNN-LSTM, the p-values for the one-way ANOVA and Tukey's HSD test dropped by almost 80%, suggesting strong significance. Increased robustness and stability were indicated by the about 80% decrease in the p-values of the Wilcoxon and Kruskal-Wallis tests.Better calibration and reliability were indicated by a 9.86% improvement in Cohen's kappa and a 52.43% decrease in the Brier score. The greater categorisation consistency was proven by a 70.27% decrease in the chi-square p-value. These findings demonstrate how the model's hyperbolic prediction architecture, adaptive optimisation, and conscious semantic learning have improved its statistical dependability and decreased error rates.

Table 3. Statistical validation of proposed and existing predictive analytics models

Model	**One-way ANOVA (p-value)**	**Tukey's HSD (p-value)**	**Cohen's Kappa**	**Kruskal–Wallis (p-value)**	**Wilcoxon Test (p-value)**	**Brier Score**	**Chi-Square (p-value)**
CNN-LSTM	0.034	0.041	0.861	0.029	0.032	0.082	0.037
Bi-GRU	0.028	0.031	0.873	0.024	0.026	0.074	0.033
BERT-DNN	0.019	0.022	0.894	0.018	0.02	0.061	0.025
Transformer-CNN	0.014	0.017	0.906	0.013	0.015	0.057	0.021
LSTM-Attention	0.01	0.013	0.918	0.009	0.011	0.051	0.018
GBERT–WASO–HH-DNN	0.006	0.008	0.946	0.005	0.007	0.039	0.011

5. Conclusion

A security-conscious analytical model (GBERT–WASO–HH-DNN) was designed to improve the accuracy of forecasting and to enhance the security of the data in workforce management systems. The model features whale-based ant colony optimisation (WASO) for optimal feature selection, hyperbolic Hopfield deep neural network (HH-DNN) for safe effective prediction analysis and Geometry-BERT (GBERT) for deep semantic feature extraction. Geometric context-based learning and adaptive optimisation enhances data representation and reduces redundancy; the hyperbolic learning mechanism facilitates convergence faster and enhances classification stability.The proposed GBERT–WASO–HH-DNN model is found to be more accurate (96.823%), more precise (95.742%), more recall (96.235%) and more F1 (96.054%) than the existing models such as CNN-LSTM, Bi-GRU, and BERT-DNN. It has been developed through experiment validation with a synthetic dataset. This model has been shown to be effective and robust through a 52.43% improvement in dependability and 39.77% reduction in convergence time. Hyperbolic forecasting, adaptive optimisation, and geometric awareness-based learning together deliver higher accuracy, uniformity and utility of real-time workforce management analysis.

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