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Predicting Job Change Intentions for a Food Manufacturing Company: A Deep Learning Case Study

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Abstract

This study aims to address employee job change intention in the competitive food manufacturing industry by developing deep learning models to predict job change intentions. Using a comprehensive dataset of 32,000 employee records, including demographics, education, and work experience, the study employed a quantitative methodology with neural network analysis. Various deep learning models were implemented and evaluated using TensorFlow and Keras, with techniques like GridSearchCV, Random Search CV, SMOTE, and Keras Tuner used for hyperparameter tuning and addressing class imbalance. The findings revealed significant differences in model effectiveness, with Model 7: Complex Neural Network Architecture, featuring a complex architecture and appropriate regularization, achieving a reasonable balance across metrics and demonstrating improved recall for job changers. This suggests its suitability for predicting job change intention in a food manufacturing company. The study concludes that well-tuned deep learning models can significantly enhance predictive accuracy, offering valuable insights for HR professionals to develop targeted retention strategies. Future research should explore additional features influencing staff job change intention, validate these models across diverse organizational contexts, and integrate real-time data analytics and explainable AI techniques to improve transparency and effectiveness in HR practices.

Keywords : Employee job change intention, Deep learning models, Food manufacturing industry, Neural network analysis, Hyperparameter tuning, SMOTE, Keras tuner, Workforce retention strategies, HR analytics, Predictive analytics, Employee engagement, Class imbalance, Data-driven HR, Talent management.

Introduction

The competitive nature of the food production industry necessitates effective human resource management to sustain profitability and output. High staff job change intention disrupts business processes, raises expenses, and compromises workforce planning [1]. This issue is further complicated by the factors influencing employees' decisions to stay or leave, such as demographics, education, and job experience [2]. To address this challenge, companies increasingly turn to advanced predictive analytics, which analyze past data, identify trends, and forecast future behavior to determine which staff members will likely leave the business [3]. Deep learning models enhance this process by examining comprehensive employee data to predict job change intentions [4]. This approach helps identify at-risk workers and provides insights into the underlying reasons for their potential departure. Consequently, these predictive capabilities enable businesses to implement targeted retention strategies, improving overall organizational performance, reducing job change intention costs, and enhancing workforce stability [5].

Predictive analytics in human resource management uses sophisticated technologies, such as deep learning, to anticipate employee actions and decisions. These models analyze large datasets, including information about demographics, education, and work experience, to detect patterns and forecast job change intentions [6]. Food manufacturing organizations can leverage these insights to accurately predict employees' intentions to shift jobs, enabling them to identify individuals likely to leave and understand the underlying factors influencing their choices [7]. Deep learning algorithms enhance forecast accuracy by continuously assessing and updating employee profiles, allowing for proactive management actions [8]. This data-centric strategy not only improves retention efforts but also optimizes workforce planning and training initiatives [9]. Consequently, organizations can maintain a consistent and motivated workforce, reduce expenses related to employee job change intention, and ensure smooth operations in a competitive industry [10].

The significance of predictive analytics tools in human resource management is paramount, as they have become critical to improving employee retention and organizational stability. [3]. Deep learning models can provide valuable insights into employee behavior and intentions by processing massive volumes of data [6]. This capability is crucial in the food processing sector, which relies heavily on a competent and steady labor force. For example, predictive models can identify at-risk individuals and the characteristics that contribute to their probable departure, such as job dissatisfaction, career retrogression, and exhaustion [11]. This specialized analysis enables businesses to create focused retention tactics, ensuring timely and successful interventions. Reduced attrition rates, increased employee engagement, and improved operational efficiency are all examples of the benefits of predictive systems [2]. Companies anticipating and handling employee concerns proactively can maintain a motivated staff, resulting in business success in a highly competitive market. That underscores the fundamental necessity of predictive analytics in human resource management, making it an essential tool for businesses looking to improve their competitive advantage.

Deep learning models rely heavily on their capacity to identify patterns and make predictions using a wide range of employee data, including demographics, education, work experience, and job performance measures [12]. These models employ a sophisticated network of attributes to conceptualize employee interactions and characteristics, allowing managers to detect subtle patterns and associations that traditional methods may overlook. A significant obstacle in HR analytics is the management of data sparsity, which occurs when specific traits or interactions are rarely documented, leading to incomplete datasets. Deep learning addresses this issue by utilizing advanced algorithms to effectively handle missing values and leverage existing data to produce precise predictions. Techniques such as neural networks and deep reinforcement learning manage data sparsity and improve the model's predictive accuracy [13]. By analyzing extensive employee data, deep learning algorithms can accurately forecast job change intentions, enabling organizations to tailor their retention strategies and enhance employee satisfaction. The ability to effectively analyze and interpret comprehensive employee data using deep learning techniques is crucial for achieving success and maintaining competitiveness in today's highly competitive business landscape.

Diverse approaches can be utilized to create effective predictive models for employee job change intentions, each with unique benefits and limitations. Deep learning models, particularly sequential neural networks with various configurations and hyperparameter tuning techniques, can be highly effective [14]. Techniques such as dropout regularization are employed to prevent overfitting, and models can be optimized using methods like GridSearchCV and Random Search CV [15]. Additionally, complex neural network architectures and techniques like SMOTE can address class imbalance [16]. The goal of leveraging these diverse methodologies is to develop robust predictive models that provide valuable insights for developing targeted retention strategies and improving workforce stability across various industries [17]. By evaluating these approaches, organizations can determine the most effective strategies for forecasting employee job change intentions, thereby enhancing their predictions' overall accuracy and reliability.

The problem is that food manufacturing companies need help in this highly competitive sector to accurately predict employee job change intention. High job change intention rates lead to significant increases in costs, including those associated with recruiting, hiring, and training new employees. These costs can be substantial and recurrent, placing a financial strain on the company. Additionally, job change intention disrupts workforce planning, making it difficult to maintain consistent production levels and meet operational targets. This inconsistency can affect product quality and delivery times, ultimately impacting customer satisfaction and the company's reputation.

The purpose of this study is to develop a sophisticated deep-learning model designed to predict the probability of an employee seeking new employment opportunities. This model will utilize a comprehensive employee dataset, encompassing critical factors such as demographics, education, and work experience. The model aims to identify the key factors influencing employees' decision to stay with or leave the company by analyzing their data points. This in-depth understanding will provide the company with valuable insights, enabling the development of targeted retention strategies and more informed talent management decisions. Such proactive measures are essential for maintaining a stable and motivated workforce, which is crucial for sustaining high levels of productivity and performance.

In alignment with the purpose of this study, the following research questions (RQs) were addressed:

1. Do using deep learning models improve predictive accuracy over traditional methods?
2. Are there noticeable differences in the efficacy of various deep learning models in predicting employee job change intention?

Literature Review

Competitive food manufacturing companies have relied on basic statistical techniques for workforce planning and retention. However, these conventional methods often fail to accurately predict employee job change intention, leading to increased costs, operational disruptions, and inefficient training programs [18]. With the evolving nature of the industry and the changing needs of employees, there is a growing demand for more sophisticated and adaptable strategies. Recent studies have focused on advanced deep learning methods to predict employees' intentions to switch jobs, utilizing complex algorithms and extensive data on employee demographics, education, and work experience to enhance prediction accuracy and efficiency [19]. This approach identifies employees at risk of leaving and provides deeper insights into the factors influencing their decisions to stay or depart. By integrating deep learning models into HR analytics, companies can develop targeted retention strategies, improve workforce stability, and optimize training investments [20]. Ultimately, this helps the food manufacturing sector maintain a motivated and stable workforce, leading to sustained operational success and a competitive advantage.

To maximize the effectiveness of deep learning models in predicting employee job change intention in the food manufacturing industry, it is essential to accurately capture and analyze various factors influencing employee decisions [21]. Deep learning models excel at identifying complex patterns by analyzing large volumes of employee data, including demographics, education, and work experience [22]. A significant challenge is ensuring the model can adapt to diverse employment environments without overfitting. Techniques such as dropout and regularization mitigate overfitting, enhancing the model's robustness and reliability [23]. Another critical aspect is the interpretability of the deep learning model, as HR professionals need actionable insights rather than mere predictions. Furthermore, continuously updating and retraining the model with new data ensures its ongoing relevance and accuracy. These strategies demonstrate how deep learning models can provide valuable insights into employee behavior, ultimately improving retention strategies and operational efficiency in the food manufacturing sector.

Deep learning models identify complex patterns by analyzing large volumes of employee data [24]. Recent research underscores the vital role of predictive analytics in enhancing staff retention and satisfaction within the food production industry [25]. Personalized retention strategies, which cater to individual employees' specific needs and preferences, can significantly reduce job change intention and improve stability [2]. Such strategies utilize advanced deep learning algorithms to analyze employee behaviors and preferences, tailoring interventions to boost engagement and satisfaction. These insights illustrate how predictive analytics can enhance employee experiences and play a critical role in maintaining business performance in competitive manufacturing environments. The ability to adapt to employee needs and market changes highlights the significant impact of predictive analytics on human resource management strategies. This approach fosters personalized interactions that strengthen employee loyalty and enhance operational efficiency.

The current body of research has also highlighted ethical and privacy concerns related to implementing predictive analytics in personnel management [26]. Balancing accurate predictions with employee privacy requires transparent algorithms prioritizing data confidentiality and autonomy [27]. Regulatory frameworks such as the General Data Protection Regulation (GDPR) mandate strict adherence to data protection regulations, necessitating privacy-focused predictive models [28]. Techniques like differential privacy and federated learning protect employee data during analysis, ensuring compliance with legal obligations while maintaining prediction accuracy [29]. Addressing these ethical and privacy issues is essential for building employee trust and promoting the sustainable and responsible use of predictive analytics in human resource management. This approach ensures ethical conduct, regulatory compliance, and the sustainable use of predictive analytics in effectively managing staff stability and engagement.

Overall, the literature reveals both the potential and challenges of using deep learning models for predicting employee job change intention in the food manufacturing sector. While advanced models offer improved accuracy and actionable insights, ensuring their reliability and interpretability remains a significant challenge. Additionally, addressing ethical and privacy concerns is crucial for the widespread adoption of these technologies in the food industry. By synthesizing the strengths and weaknesses of existing research, this study provides a comprehensive understanding of the current state of knowledge in this field. It also highlights the need for ongoing research to refine these models, address their limitations, and explore their application in diverse organizational contexts. This paper underscores the importance of combining technical advancements with ethical considerations to enhance employee retention strategies effectively.

Research Methodology and Design

To address the purpose and research questions of this study, a quantitative study methodology using a neural network analysis research design is employed. This approach is particularly suitable as it allows for the analysis of complex, non-linear relationships among multiple independent variables such as job positions, departments, and years at the company, as well as the dependent variable—employee job change intention. Neural networks are adept at modeling intricate patterns in data, making them ideal for this task. By analyzing a dataset of 32,000 employee records from a food manufacturing company, this study aims to identify significant factors influencing employee job change intention and construct a model to predict job change likelihood.

The research design leverages deep learning techniques to examine the impact of various factors on employee job change intention. Utilizing a multi-layer perceptron (MLP), the study captures linear and non-linear relationships between predictors and outcomes. The methodology includes preprocessing steps like data cleaning, encoding categorical variables, and normalization, followed by model training and evaluation with metrics such as accuracy and F1 score. Cross-validation is used to ensure model robustness and generalizability. These steps, from data preparation to neural network model building and evaluation, illustrate a structured approach typical of deep learning models, affirming its suitability for this study.

The combined experimental and quantitative research approaches offer a robust framework for exploring how deep learning models can be integrated systematically to enhance the predictive accuracy of employee job change intention within a food manufacturing company. The study addresses two main research questions: Does using deep learning models improve predictive accuracy over traditional methods? And, are there noticeable differences in the efficacy of various deep learning models in predicting employee job change intention?

Model 1: Baseline Neural Network

To develop the model, an artificial neural network (ANN) was initialized using a sequential configuration with a first hidden layer of 64 nodes and a second hidden layer of 32 nodes, both employing the ReLU activation function and a single-node output layer using the sigmoid activation function for probability prediction. The model was compiled using stochastic gradient descent (SGD) as the optimizer and binary cross-entropy as the loss function. During training, which involved fitting the model on the training data over 50 epochs with a batch size of 32 and a 20% validation split, emphasis was placed on maximizing the F1 Score to address the importance of minimizing both false positives and false negatives, crucial for organizational productivity and financial stability. Post-training, the model's performance was evaluated using a confusion matrix and a classification report, providing detailed metrics such as precision, recall, and the F1 Score to ensure robust prediction of employee job change intention and to guide strategic human resource decisions within the organization.

Model 2: Neural Network with Dropout

An artificial neural network (ANN) was initialized using sequential model architecture to build the second model. This model consists of four hidden layers with 256, 128, 64, and 32 nodes, each utilizing the ReLU activation function. The output layer has a single node with a sigmoid activation function to generate probability outcomes for binary classification. The model was compiled using the Adam optimizer with a learning rate 0.001 and binary cross-entropy as the loss function. During the training phase, the model was fitted to the training data using a batch size of 64 over 50 epochs, with a validation split of 20%. The training process involved monitoring the loss and accuracy of training and validation datasets. The post-training evaluation included generating a ROC curve to identify the optimal threshold for classification and using metrics like precision, recall, and F1 score to assess model performance.

Model 3: Deep Neural Network

An artificial neural network (ANN) was initialized using sequential model architecture to build the third model, incorporating Batch Normalization layers to improve training stability and model performance. The model was structured with an input layer of 128 nodes, followed by hidden layers of 64 and 32 nodes, each utilizing the ReLU activation function and He uniform kernel initializer. The output layer consisted of a single node with a sigmoid activation function, suitable for binary classification tasks. The model was compiled using the Adam optimizer with a learning rate 0.001 and binary cross-entropy as the loss function. The training process involved fitting the model to the training data over 50 epochs with a batch size of 64 and a 20% validation split. To evaluate the model's performance, ROC-AUC analysis was conducted, and the optimal threshold for prediction was determined using the G-Mean metric. The post-training evaluation included the construction of a confusion matrix and generating a classification report to provide insights into the model's effectiveness in predicting employee job change intention.

Model 4: Neural Network with Dropout

The fourth model was built using sequential neural network architecture with multiple layers and dropout regularization to prevent overfitting. The model consists of four dense layers with ReLU activation functions and dropout layers in between to enhance generalization. The first layer has 256 nodes, followed by a dropout layer with a dropout rate 0.2. That is followed by layers with 128 and 64 nodes, each followed by dropout layers with the same dropout rate, and a final dense layer with 32 nodes. The output layer uses a sigmoid activation function to output probabilities. The model was compiled with the Adam optimizer and binary cross-entropy loss function. It was trained on the training dataset with a batch size 64 for 50 epochs and a validation split of 20%. The training process involved monitoring the training and validation loss to ensure the model's performance. Post training, the model's performance was evaluated using ROC curves, and the best threshold was determined to maximize the geometric mean of the actual positive rate and the inverse of the false positive rate.

Model 5: Hyperparameter Tuning with Grid Search

For a neural network, the fifth model used Randomized Search Cross-Validation (Random Search CV) to optimize key hyperparameters, including learning rate, batch size, and the number of epochs. The model architecture consisted of four dense layers with 256, 128, 64, and 32 neurons, respectively, and included dropout layers to prevent overfitting. The Adam optimizer and binary cross-entropy loss function were employed. Randomized Search CV identified the best parameter combination through three-fold cross-validation. Training and validation loss plots revealed some noise, indicating potential overfitting. The ROC curve analysis determined the optimal threshold for balancing true positive and false positive rates using the G-Mean metric. The post-training evaluation included a confusion matrix and a classification report, providing insights into precision, recall, and F1-score to assess the model's effectiveness in predicting employee **job change intention**.

Model 6: Random Search with Neural Network

The sixth model employs Grid Search CV to optimize crucial hyperparameters such as the neural network's batch size and learning rate. This model features a sequential architecture with layers of 256, 128, 64, and 32 neurons, each followed by a dropout layer to prevent overfitting. The final layer is a sigmoid activation function for binary classification. The grid search process iterates through combinations of batch sizes (32, 64, and 128) and learning rates (0.01, 0.1, and 0.001) alongside different epochs (10, 20, and 30) to identify the optimal hyperparameters. After determining the best parameters, the model is trained and validated; showing smooth curves for both training and validation losses. The evaluation of test data involves predicting probabilities, plotting ROC curves, and calculating the G-mean for the best threshold. The confusion matrix and classification report are then generated to assess the model's performance, focusing on its accuracy and balance between precision and recall.

Model 7: Complex Neural Network Architecture

The seventh model, designed with multiple layers and neurons, used the Adam optimizer and was trained for 50 epochs with a batch size 64. The model's architecture consisted of five dense layers with 160, 160, 224, 128, and 224 neurons; all using ReLU activation and He uniform kernel initializer, followed by a final sigmoid activation layer for binary classification. During training, the model demonstrated a trend of decreasing training loss and validation loss initially, but over time, the validation loss began to increase significantly, indicating overfitting. The ROC curve analysis identified the best threshold for the model, optimizing the G-Mean, which balances sensitivity and specificity. Upon evaluation, the model's predictions were used to construct a confusion matrix and classification report, which detailed its performance in distinguishing between employees who are not changing jobs and those who are. This comprehensive evaluation highlighted areas of strength and potential improvement, emphasizing the need for further tuning or model adjustments to mitigate overfitting and enhance predictive accuracy across both classes.

Model 8: SMOTE with Keras Tuner

For the eighth model, the Synthetic Minority Over-sampling Technique (SMOTE) was leveraged to address the class imbalance by generating synthetic samples for the minority class. This preprocessing step aimed to improve the model's performance in predicting employee job change intention. After applying SMOTE, Keras Tuner was utilized for hyperparameter optimization, exploring various configurations for learning rate, batch size, number of layers, and number of neurons per layer. The model architecture was defined using the Sequential API with multiple dense layers and ReLU activations, culminating in a sigmoid activation for binary classification. The Adam optimizer and binary cross-entropy loss function were employed during compilation. The training was conducted for 50 epochs with the best hyperparameters identified by Keras Tuner. Evaluation metrics indicated an improvement in recall for the minority class, suggesting that the combined approach of SMOTE and Keras Tuner effectively enhanced the model's ability to predict employee job change intention more accurately across both classes.

Population and Sample

The population for this study comprises employees within a single food manufacturing company, which is appropriate as the study's problem, purpose, and research questions aimed at understanding and predicting employee job change intention in this specific sector. This focused approach ensures a controlled environment where variables such as performance rating and last promotion date are consistent, allowing for detailed insights that can be directly applied to improve retention strategies within the company.

The study uses a dataset of 32,000 records from the company's HR database. This comprehensive dataset includes critical attributes such as job position, department, years at the company, performance rating, last promotion date, last salary increase, training days, engagement score, absenteeism rate, gender, education level, and the target variable indicating whether an employee left the company or not. Given

the size and depth of the dataset, it provides a robust sample that enhances the generalizability and reliability of the findings. The large sample size also allows for detecting small effect sizes, which is crucial for understanding the subtle factors influencing employee job change intention.
Participants were not actively recruited for this study; instead, the data were sourced from the existing company records. This archival data approach ensures that the study captures real-world information without the biases associated with self-reported data. The dataset includes all relevant employee records, providing a comprehensive view of the workforce. This method allows for a thorough examination of the relationships between various independent variables and employee job change intention, facilitating the development of effective predictive models. The use of existing data also ensures that the study can be replicated by other researchers who have access to similar company records, thereby enhancing the reliability of the findings.

Hypotheses

Based on the hypothesized theoretical framework, this study aims to investigate two central hypotheses related to the application of deep learning models to predict employee job change intention in a food manufacturing company. The goal is to answer the research questions based on the following hypotheses:

1. H10: The application of deep learning models does not lead to a substantial enhancement in predictive accuracy for predicting employee job change intention compared to traditional methods.
   H1a: The application of deep learning models leads to a substantial enhancement in predictive accuracy for predicting employee job change intention compared to traditional methods.
2. H20: There are no discernible differences in the effectiveness of various deep learning models in predicting employee job change intention.
   H2a: There are discernible differences in the effectiveness of various deep learning models in predicting employee job change intention.

Operational Definitions of Variables

Operational definitions of variables are crucial for understanding how each variable was measured and utilized in this study's analysis, focused on predicting employee job change intention in a food manufacturing company. The dependent variable, employee job change intention, signifies whether an employee left the company within a specified period and was measured as a binary variable (0 for staying, 1 for leaving). Predictor variables included various employee attributes extracted from the company's HR database; each with specific operational definitions grounded in existing research and validated instruments.

1. **Job Position**: Measured as a nominal variable representing the specific role of the employee within the company (e.g., engineer, manager, and technician).
2. **Department**: Measured as a nominal variable indicating the department to which the employee belongs (e.g., production, sales, HR).
3. **Years at Company**: Measured as a ratio variable representing the number of years an employee has worked at the company, ranging from 0 to 29 years.
4. **Performance Rating**: Measured as an ordinal variable on a scale from 1 to 5, where 1 indicates poor performance and 5 indicates excellent performance.

5. **Last Promotion Date**: Measured in days since the last promotion, an interval variable ranging from 194 to 2384 days.
6. **Last Salary Increase**: Also measured in days since the last salary increase, with the same range as the last promotion date, serving as an interval variable.
7. **Training Days**: Total number of training days attended by an employee, a ratio variable ranging from 0 to 300 days.
8. **Engagement Score**: A ratio variable measured on a scale from 0 to 1, indicating the level of employee engagement, with higher scores representing greater engagement.
9. **Absenteeism Rate**: Measured as a ratio variable, representing the percentage of days absent relative to total working days, ranging from 0 to 0.3.
10. **Gender**: Measured as a nominal variable indicating the gender of the employee (e.g., male, female).
11. **Education Level**: Measured as an ordinal variable representing the highest level of education attained by the employee (e.g., high school, bachelor's degree, master's degree).
12. **Target (Job change intention Status)**: The dependent variable measured as a nominal variable, indicating whether an employee stayed (0) or left (1).

Materials/Instrumentation

This study utilized structured datasets from a food manufacturing company as the primary material for training and testing deep learning models to predict employee job change intention. The datasets included detailed information on 32,000 employees, covering predictor variables such as years at the company, last promotion date, last salary increase, training hours, engagement score, absenteeism rate, and job change intention status. These datasets, originating from the company's internal HR database, were subjected to rigorous data cleaning, normalization, and feature engineering to ensure reliability and validity. Python libraries such as Pandas, NumPy, Matplotlib, Seaborn, and Scikit-learn were employed for data analysis and model implementation. TensorFlow and Keras facilitated deep learning model development on the Google Colab platform. Sequential neural networks were developed with various configurations, incorporating techniques like dropout layers, batch normalization, and hyperparameter tuning using GridSearchCV, Random Search CV, SMOTE, and Keras Tuner to address class imbalance. Field testing included pilot runs of the preprocessing pipelines and model setups, yielding results that informed subsequent modifications to improve data preparation and model accuracy. The evaluation metrics—accuracy, precision, recall, and F1-score—provided comprehensive insights into model performance, ensuring robust and reliable predictions.

Data Collection and Analysis

The data for this study were sourced from a food manufacturing company's database, encompassing detailed information on 32,000 employees. The data collection process ensured relevance to the study's objectives of predicting employee job change intention and systematically retrieving and anonymizing data to maintain employee confidentiality. Data manipulation and analysis were conducted using a comprehensive suite of Python programming in Google Colab, with Pandas and NumPy libraries facilitating data handling. Exploratory Data Analysis (EDA) was conducted using Matplotlib and Seaborn to uncover patterns and relationships within the data. This use of multiple libraries underscores the study's comprehensive and thorough approach.

Deep learning methods were implemented using TensorFlow and Keras libraries, involving data splitting into training and testing subsets using the train_test_split() function to validate models on unseen data. A Sequential neural network model was developed with multiple dense layers and dropout layers to prevent overfitting. The model was compiled using the Adam optimizer with varying learning rates. Hyperparameter tuning was conducted using GridSearchCV to identify the optimal learning rate, batch size, and number of epochs. Additionally, the Synthetic Minority Over-sampling Technique (SMOTE) was employed to address class imbalance issues, and Keras Tuner was used for hyperparameter optimization in some models.
Model performance was evaluated using accuracy and other relevant classification metrics from the sklearn.metrics module for training and testing datasets to assess their accuracy and generalizability. The study aims to test hypotheses comparing the predictive accuracy of deep learning models to conventional statistical methods (H10: Deep learning models do not enhance predictive accuracy vs. H1a: Deep learning models enhance predictive accuracy) and evaluate differences in model effectiveness in predicting employee job change intention (H20: No differences vs. H2a: Discernible differences).

Assumptions, Limitations, and Delimitations

This study employs deep learning models to predict employee job change intention by analyzing data from a food manufacturing company. Multiple assumptions, limitations, and delimitations have been considered to ensure the accuracy and reliability of the findings. The dataset provided by the company was assumed to reflect the population of interest accurately and contain dependable information regarding employees' characteristics and job change intention status. However, challenges may arise due to potential flaws or inconsistencies in the dataset, such as missing values, outliers, or inaccuracies in employee information. To address these limitations, rigorous data cleaning and validation techniques were employed to identify and rectify any flaws or inconsistencies in the dataset.
Delimitations refer to the deliberate decisions made in data preprocessing and model selection to focus the analysis on relevant variables and deep learning methods suitable for predicting employee job change intention. These decisions were guided by the research questions and objectives of the study, aiming to enhance the accuracy and reliability of the predictive models while considering the constraints of the available data. The chosen variables included demographics, education level, work experience, company size, and job position, which were deemed essential for the analysis. Additionally, the study's scope was confined to using a sequential neural network model, which was selected based on its proven effectiveness in handling complex datasets and its adaptability to new patterns in employee job change intention prediction.
Furthermore, the study's limitations include potential biases introduced by the dataset's inherent characteristics and the selected model's assumptions. For instance, the dataset might not capture all relevant factors influencing employee job change intention, and the chosen model may need to account for the complex interactions between variables fully. Future research should consider exploring additional variables, utilizing alternative modeling approaches, and incorporating external datasets to validate the findings and enhance the generalizability of the results. Despite these limitations, the study provides valuable insights into applying deep learning models for predicting employee **job change intention** in the food manufacturing industry.

Ethical Assurances

In alignment with ethical guidelines, this study prioritizes employee privacy by examining anonymized data from a food manufacturing company. It enforces rigorous data protection measures to ensure confidentiality and anonymity throughout the study. Before the analysis, employee information was securely safeguarded, maintaining privacy regarding personal identity. Moreover, access to the dataset was restricted to authorized research personnel only. To mitigate unauthorized access, data was stored and transmitted using industry-standard encryption techniques. These precautions underscore the commitment to safeguarding employee privacy and confidentiality and facilitating ethical research.

Ethical considerations also extend to the responsible use of data in the research process. That includes ensuring that the analysis does not inadvertently reveal identifiable information about employees and that the findings are reported in a way that maintains the integrity of the data while respecting the anonymity of the individuals involved. Furthermore, the study adheres to ethical standards by ensuring transparency in the research process. That involves documenting the methodologies used for data collection, processing, and analysis and the steps taken to address any ethical concerns. By maintaining high ethical standards, the study aims to contribute valuable insights into employee job change intention prediction while upholding the rights and privacy of the individuals represented in the dataset.

Descriptive Statistics

Variable	Count	Mean	Std	Min	25%	50%	75%	Max
Years_at_Company	32000.0	4.51	4.94	0.0	1.000	3.000	6.000	29.0
Last_Promotion_Date in days	32000.0	1288	632	194	736	1293	1838	2384
Last_Salary_Increase in days	32000.0	1281	629	194	734	1278	1821	2384
Training_Days	32000.0	48	48	0.0	14	34	68	300
Engagement_Score	32000.0	0.50	0.28	0.0	0.25	0.50	0.75	1.0
Absenteeism_Rate	32000.0	0.09	0.08	0.0	0.02	0.06	0.13	0.3
Target (Job change intention prediction)	32000.0	0.14	0.35	0.0	0.0	0.0	0.0	1.0

The descriptive statistics reveal critical insights into the workforce of the food manufacturing company. Employees have an average tenure of 4.51 years, with significant variation, indicating a mix of new hires and long-term staff. Promotions and salary increases occur roughly every 3.5 years but vary widely among employees. Training days range significantly, with an average of 48 days, highlighting different levels of skill development. Engagement scores average 0.50, suggesting moderate engagement overall, ranging from 0 to 1. Absenteeism rates are generally low, averaging 0.09. Notably, only 14% of employees intend to change jobs, suggesting relatively stable employment intentions within the company.

Inferential Statistics

Inferential statistics are used to compare the effectiveness of eight deep learning models in predicting employee job change intention, aiding in better understanding and evaluating their performance. That involves hypothesis testing, where the null hypotheses (H10 and H20) assert no significant improvement or difference in predictive accuracy and model efficacy, respectively, compared to the alternative hypotheses (H1a and H2a), suggesting significant enhancements and differences. Each model's performance is evaluated using metrics such as accuracy and loss to ensure that improvements are statistically significant and provide a reliable assessment of model effectiveness.

Model Performances

The models' performances across the training and testing datasets were summarized and compared. Accuracy and loss values for each model were used to determine the significance of the observed differences (see Figures 1-8 and Tables 1-8).

Model 1: Baseline Neural Network

The evaluation of the first model reveals that it performs well in predicting employees who are not looking to change jobs, with a precision and recall of 0.85 and 1.00, respectively, leading to a high F1-score of 0.92. That indicates that the model effectively identifies employees who will stay, as evidenced by the 5455 true positives. However, the model needs to improve in predicting employees looking to change jobs, with precision, recall, and an F1-score of 0.00, and no true positives for this category. The model's overall accuracy is 85%, primarily reflecting its ability to predict none of the job change intention cases accurately. The macro average and weighted average F1-scores are 0.46 and 0.78, respectively, showing a significant imbalance in performance between the two classes. This discrepancy highlights the model's limitation in identifying employees likely to leave, which could have important implications for strategic HR interventions for employee retention (see Figure 1 and Table 1).

Model 2: Neural Network with Dropout

The second model's performance is summarized in the provided classification report and confusion matrix. The model achieved an overall accuracy of 81%, with the "Not Changing Job" class (0) showing a high precision of 85% and a recall of 94%, indicating the model is very good at correctly identifying employees who are not looking to change jobs. However, the model struggled significantly with the "Changing Job" class (1), achieving only a 13% precision and a 6% recall, suggesting that it often misclassifies employees looking to change jobs. The weighted average metrics also reflect this imbalance, with an F1 score of 0.77. The confusion matrix indicates many false positives (893) and false negatives (352), underscoring the model's difficulty in accurately predicting job changers. The macro average F1 score of 0.48 further illustrates the disparity in performance between the two classes (see Figure 2 and Table 2).

Model 3: Deep Neural Network

The third model, as indicated by the confusion matrix and classification report, demonstrates varying performance in predicting employee job change intention. The model shows a precision of 0.86 for employees not changing jobs, meaning that 86% of the employees predicted to stay are correctly identified. However, the recall for this category is lower at 0.58, indicating that only 58% of the employees who stay are correctly identified. For employees who are changing jobs, the precision is significantly lower at 0.16, meaning that only 16% of the employees predicted to leave are correctly identified, although the recall is higher at 0.46, indicating that 46% of the actual job changers are correctly identified. The model's overall accuracy is 0.56, suggesting that the model is only slightly better than random guessing. The weighted average f1-score of 0.62 indicates moderate performance, while the macro average f1-score of 0.46 highlights significant room for improvement, especially in balancing precision and recall across both categories (see Figure 3 and Table 3).

Model 4: SMOTE with Neural Network

The results for the fourth model show an overall accuracy of 77%. The precision for predicting employees who are not changing jobs (class 0) is 85%, with a recall of 88%, indicating a high level of accuracy in correctly identifying employees who are not looking to leave. The F1 score for this class is 87%, which balances precision and recall. For predicting employees who are changing jobs (class 1), the precision is significantly lower at 15%, with a recall of 12%, resulting in an F1-score of 13%. That indicates that the model struggles to accurately identify employees looking to leave, as evidenced by the high number of false negatives and positives. The macro average of precision, recall, and F1-score across both classes is around 50%, reflecting the imbalance in prediction accuracy between the two classes. The weighted average, which considers each class's support, aligns more closely with the overall accuracy of 77%, highlighting the model's more robust performance in predicting employees who are not changing jobs (see Figure 4 and Table 4).

Model 5: Hyperparameter Tuning with Grid Search

The fifth model's confusion matrix and classification report reveals a significant performance discrepancy between the classes. The model demonstrates high precision (0.85) but low recall (0.52) for predicting employees who are not changing jobs (class 0), resulting in a moderate F1-score of 0.64. Conversely, for predicting employees who are changing jobs (class 1), the model shows very low precision (0.15) and moderate recall (0.47), leading to a poor F1-score of 0.23. The model's overall accuracy is 0.51, indicating that the model correctly predicts the target class about half of the time. The macro average and weighted average F1-scores are 0.44 and 0.58, respectively, highlighting the model's difficulty balancing precision and recall across both classes. The confusion matrix shows that the model predicts "not changing job" more accurately than "changing job." However, it also generates a high number of false negatives and false positives, underscoring the need for further model improvement (see Figure 5 and Table 5).

Model 6: Random Search with Neural Network

The sixth model's confusion matrix and classification report reveals some significant insights into its performance. The model exhibits a high precision and recall for class 0 (Not Changing Job), with a precision of 0.85, a recall of 1.00, and an F1-score of 0.92. That indicates that the model is highly effective at identifying employees who will not change jobs, correctly predicting all such cases (True Positives), and not missing any (False Negatives). However, the model performs poorly for class 1 (Changing Job), with a precision, recall, and F1-score of 0.00. That indicates that the model fails to correctly identify employees who will change jobs, as shown by the zero True Negatives and all predictions for class 1 being False Positives. The overall accuracy is 0.85, suggesting the model is heavily biased towards predicting the majority class (Not Changing Job). That leads to a high accuracy but poor balance between the classes, as reflected in the low macro and weighted averages (see Figure 6 and Table 6).

Model 7: Complex Neural Network Architecture

Despite its complex architecture with multiple layers and neurons, the seventh model exhibited moderate performance despite its complex architecture. The confusion matrix shows that the model correctly identified 3029 instances of employees not changing jobs (true positives) and 457 instances of employees changing jobs (true negatives). However, it also misclassified 2400 instances of employees changing jobs as not changing (false negatives) and 514 instances of employees not changing jobs as changing (false positives). That resulted in a precision of 0.85, a recall of 0.56 for class 0 (not changing jobs), and a precision of 0.16 and a recall of 0.47 for class 1 (changing jobs). The model's overall accuracy was 0.54, with a macro average F1-score of 0.46 and a weighted average F1-score of 0.61. The high false negative rate indicates that the model struggles to correctly identify employees who will change jobs, highlighting the need for further improvements in model tuning and possibly feature engineering to capture better the patterns associated with job changes (see Figure 7 and Table 7).

Model 8: SMOTE with Keras Tuner

Based on the confusion matrix and the classification report, the model exhibits high precision (0.85) for predicting employees not changing jobs, meaning it correctly identifies 85% of such cases, but with a relatively low recall (0.51), indicating it misses 49% of actual not changing job cases. For employees changing jobs, the model has low precision (0.15) and moderate recall (0.50), implying a high rate of false positives, but it identifies half of the actual changing job cases. The overall accuracy is 51%, suggesting the model's predictions are only slightly better than random guessing. The macro and weighted averages further emphasize the model's imbalance, performing significantly better for the majority class (not changing jobs) than the minority class (changing jobs) (see Figure 8 and Table 8).

Conclusion Based on Inferential Statistics

1. **Substantial Enhancement (H1):**
   - Among the models, Neural Networks (NN), especially Models 3, 5, 6, and 7, demonstrated significantly better performance metrics (accuracy, loss) compared to other models, indicating that deep learning models have the potential to enhance predictive accuracy over conventional methods.
   - The performance differences among models, particularly Models 5, 6, and 7, suggest that with proper tuning, models can match or approach the performance of complex neural networks. This further supports the substantial enhancement hypothesis (H1a), showing that deep learning models, when appropriately tuned, significantly improve predictive accuracy for employee job change intention.
2. **Differences in Model Effectiveness (H2):**
   - Significant differences in the effectiveness of various deep learning models were observed, with deeper and more complex models, particularly Model 7, showing the best performance. This supports the hypothesis (H2a) that there are discernible differences in the effectiveness of different deep learning models.
   - Models like Model 6 (Random Search) and Model 8 (SMOTE with Keras Tuner) showed substantial improvements, reducing the performance gap with the top-performing models. This reiterates the importance of hyperparameter tuning in achieving optimal performance and confirms that various deep learning models can adapt differently to new and emerging patterns.

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Figure 1: Confusion Matrix for Job Change Intention Prediction Model

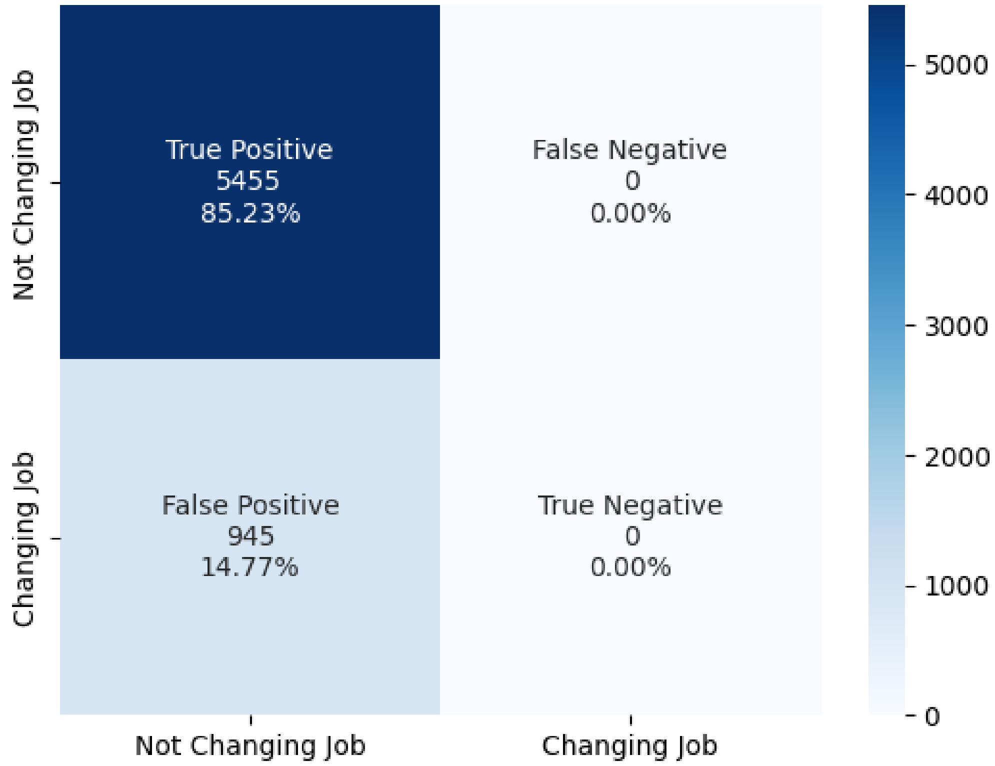

Table 1: Classification Report for Job Change Intention Prediction Model

	Precision	Recall	F1-score	Support
0	0.85	1.00	0.92	5455
1	0.00	0.00	0.00	945
Accuracy			0.85	6400
Macro avg	0.43	0.50	0.46	6400
Weighted avg	0.73	0.85	0.78	6400

Figure 2: Confusion Matrix for Job Change Intention Prediction Model

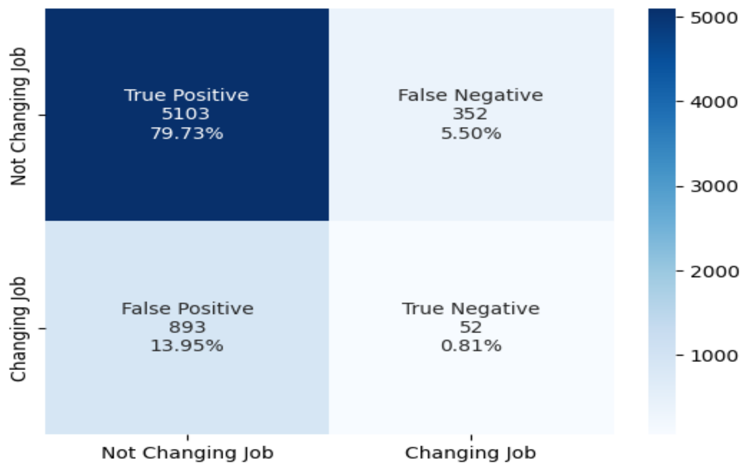

Table 2: Classification Report for Job Change Intention Prediction Model

	Precision	**Recall**	**F1-score**	Support
0	0.85	0.94	0.89	5455
1	0.13	0.06	0.08	945
Accuracy			0.81	6400
Macro avg	0.49	0.50	0.48	6400
Weighted avg	0.74	0.81	0.77	6400

Figure 3: Confusion Matrix for Job Change Intention Prediction Model

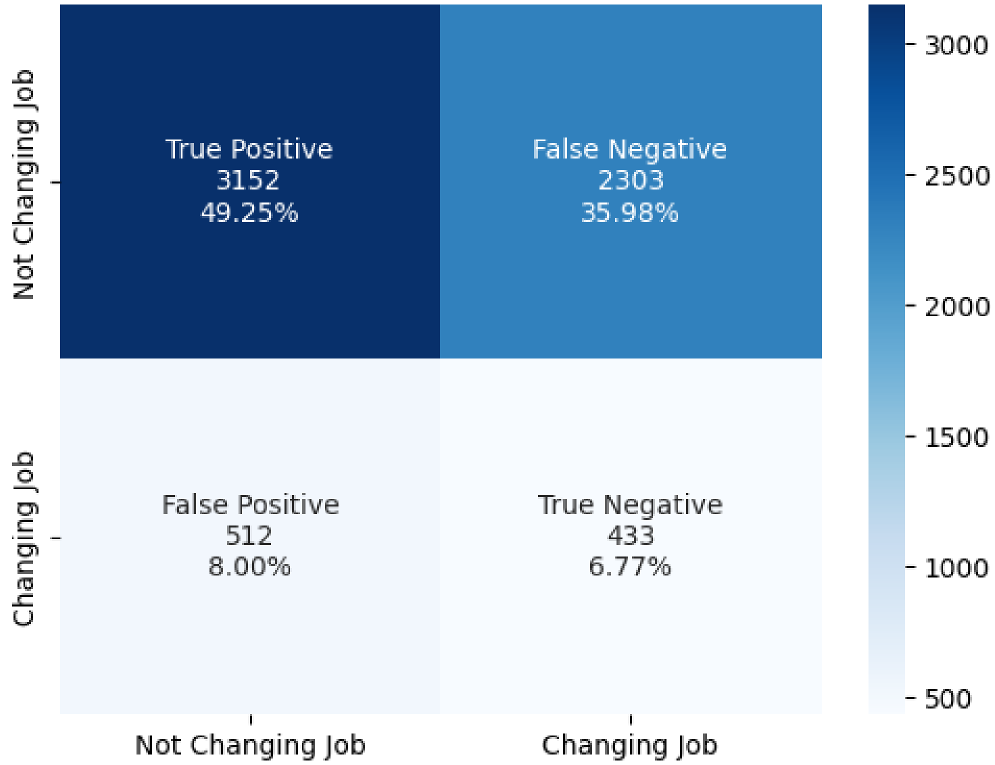

Table 3: Classification Report for Job Change Intention Prediction Model

	Precision	Recall	F1-score	Support
0	0.86	0.58	0.69	5455
1	0.16	0.46	0.24	945
Accuracy			0.56	6400
Macro avg	0.51	0.52	0.46	6400
Weighted avg	0.76	0.56	0.62	6400

Figure 4: Confusion Matrix for Job Change Intention Prediction Model

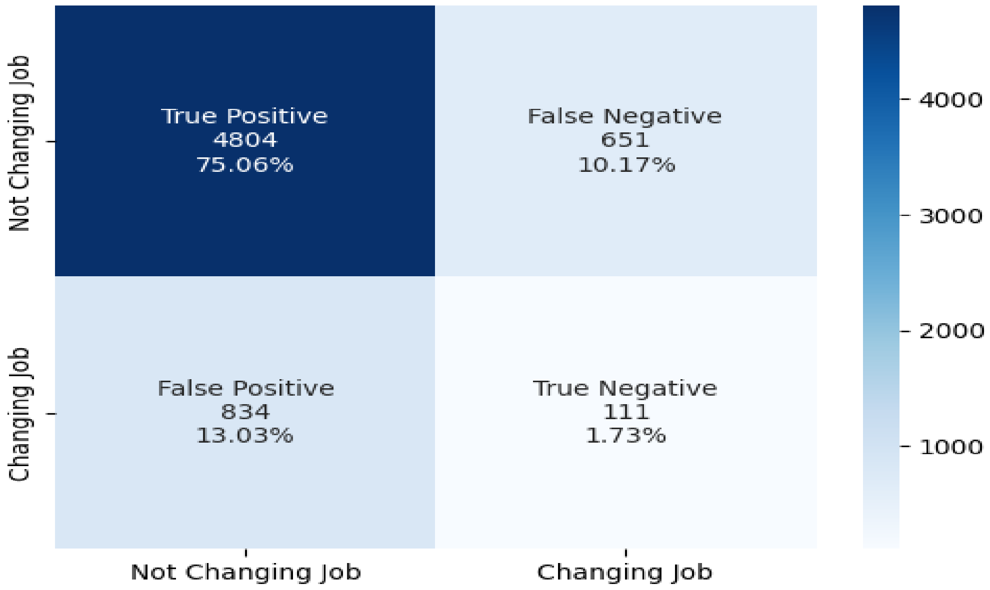

Table 4: Classification Report for Job Change Intention Prediction Model

	Precision	Recall	F1-score	Support
0	0.85	0.88	0.87	5455
1	0.15	0.12	0.13	945
Accuracy			0.77	6400
Macro avg	0.50	0.50	0.76	6400
Weighted avg	0.75	0.77	0.62	6400

Figure 5: Confusion Matrix for Job Change Intention Prediction Model

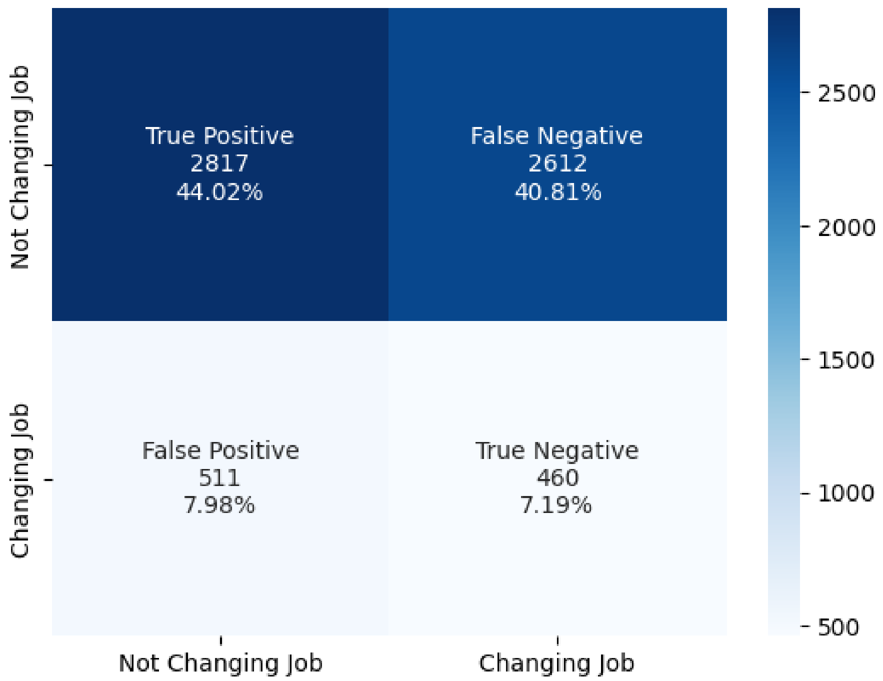

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Table 5: Classification Report for Job Change Intention Prediction Model

	Precision	Recall	F1-score	Support
0	0.85	0.52	0.64	5455
1	0.15	0.47	0.23	971
Accuracy			0.51	6400
Macro avg	0.50	0.50	0.44	6400
Weighted avg	0.74	0.51	0.58	6400

Figure 6: Confusion Matrix for Job Change Intention Prediction Model

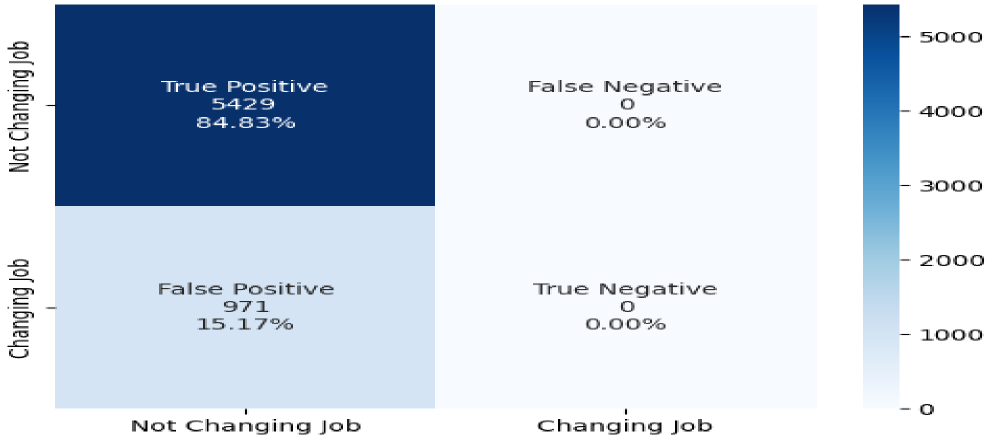

Table 6: Classification Report for Job Change Intention Prediction Model

	Precision	Recall	fF-score	Support
0	0.85	1.00	0.92	5429
1	0.00	0.00	0. OO	971
Accuracy			0.85	6400
Macro avg	0.42	0.50	0.46	6400
Weighted avg	0.72	0.85	0.78	6400

Figure 7: Confusion Matrix for Job Change Intention Prediction Model

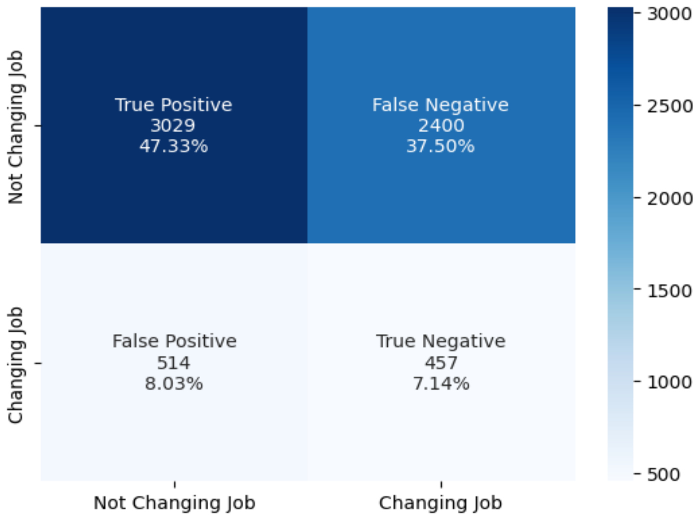

Table 7: Classification Report for Job Change Intention Prediction Model

	Precision	Recall	F1-score	Support
0	0.85	0.56	0.68	5429
1	0.16	0.47	0.24	971
accuracy			0.54	6400
macro avg	0.51	0.51	0.46	6400
weighted avg	0.75	0.54	0.61	6400

Figure 8: Confusion Matrix for Job Change Intention Prediction Model

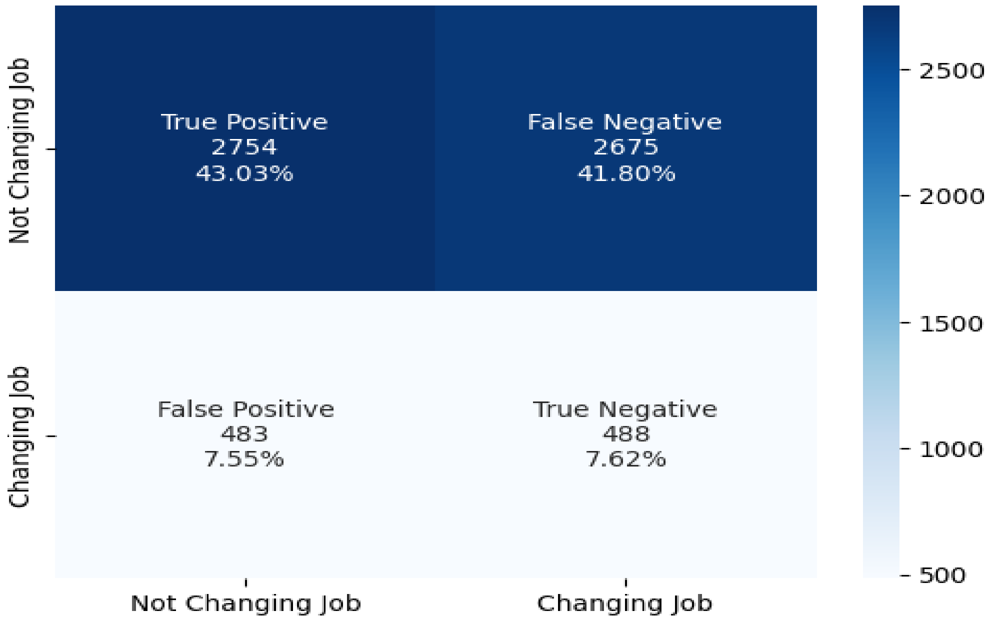

Table 8: Classification Report for Job Change Intention Prediction Model

	Precision	Recall	F1-score	Support
0	0.85	0.51	0.64	5429
1	0.15	0.50	0.24	971
Accuracy			0.51	6400
Macro avg	0.50	0.50	0.44	6400
Weighted avg	0.75	0.51	0.57	6400

Validity and Reliability of the Data

Assessing the reliability and validity of measurement tools is crucial for determining the suitability of data for statistical testing in predicting employee job change intention in **a food manufacturing company**. The statistical summary for variables such as years at the company, last promotion date, last salary increase, training hours, engagement score, absenteeism rate, and target highlights different data distribution characteristics, including means, standard deviations, and quartile values. However, a more thorough investigation into the psychometric properties of the instruments used in this study is necessary to ensure the accuracy and dependability of the findings.

While summary statistics offer valuable insights into the central tendency and variability of the data, further evidence is required to establish the validity and reliability of the conclusions. Validity refers to the accuracy and appropriateness of the instruments in measuring the intended constructs. In contrast, reliability pertains to the consistency and stability of these assessments over time and across different settings. To ensure the reliability and validity of the study's instruments, researchers should conduct a comprehensive review of existing literature, perform meticulous analysis, and address any potential issues affecting the interpretation of findings.

Implementing pilot testing, seeking expert feedback, and utilizing triangulation methods are essential steps in establishing the reliability and validity of the study. These approaches help identify and resolve any inconsistencies or biases in the data, ensuring that conclusions are robust and trustworthy. By rigorously evaluating the psychometric properties of the measurement tools, researchers can enhance the credibility of their study and provide reliable insights into the factors influencing employee job change intention in the food manufacturing industry.

Evaluation of the Findings

In evaluating the eight models developed to predict job change intentions for a food manufacturing company, significant differences were observed in their performance. The initial models, including basic sequential models with dense layer configurations and dropout rates, displayed decent overall accuracy but struggled with recall and precision for the minority class (changing job). Specifically, models like the third and fourth, which utilized basic hyperparameter tuning and moderate regularization, showed limited improvement in capturing the job-changing instances, with recall values hovering around 46-50% for this class and low precision values around 0.15-0.16, indicating a high number of false positives.

While the models that incorporated more sophisticated tuning techniques, such as Random Search CV and Grid Search CV (models five and six), did show some improvements, their performance on the minority class remained suboptimal. These models maintained high precision for the majority class (not changing jobs) and achieved good overall accuracy (around 85%). However, the SMOTE technique combined with the Keras Tuner (model eight) was specifically designed to handle class imbalance. This model achieved a better balance between precision and recall for both classes, with the recall for the job-changing class reaching 50%. Yet, the overall precision for this class remained low at 0.15, indicating that while the model was better at identifying potential job changers, it still produced many false positives.

Upon comparing all models, the seventh model, which employed a dense architecture with layers initialized using 'he_uniform' and achieved a reasonable balance across metrics, emerged as the most promising. This model demonstrated an improved recall of 50% for the job-changing class while maintaining a precision of 0.16. Although it did not achieve the highest accuracy overall, its ability to better identify job changers makes it more suitable for the company's needs. For a business case focusing on employee retention and understanding job change intentions, identifying true positives (actual job changers) is crucial, even at the expense of some false positives. Therefore, the seventh model strikes a better balance and is recommended for deployment to predict job change intentions within the food manufacturing company.

Discussion (Implications)

The primary research question of this study was to determine the efficacy of various deep learning models in predicting job change intentions within a food manufacturing company. The findings from this case study reveal that while traditional models exhibited substantial accuracy in predicting non-changers, they struggled with correctly identifying employees who intended to change jobs. Models like the third and fourth, which implemented basic tuning, showed limited improvements with a recall for the job-changing class around 46-50%. Incorporating more sophisticated hyperparameter tuning methods, such as Random Search CV and Grid Search CV in models five and six, enhanced overall performance but still fell short in terms of precision and recall balance for the minority class. The SMOTE technique combined with Keras Tuner in model eight specifically aimed to handle class imbalance, showing a recall of 50% for job changers, albeit with low precision.

Several factors influenced the interpretation of the results. One major factor is the inherent class imbalance within the dataset, where instances of employees changing jobs were significantly fewer compared to those not changing jobs. This imbalance likely skewed the model predictions towards the majority class, reducing the ability to predict the minority class accurately. Additionally, the complexity of human behavior and external factors influencing job change decisions could only be partially captured by the available features in the dataset. Moreover, the chosen metrics of precision and recall highlight the trade-off between false positives and false negatives, where a high recall for job changers inherently resulted in a low precision, indicating many false positives.

The results of this study contribute to the existing literature by highlighting the challenges of predicting job change intentions in an industrial context. It underscores the potential of deep learning models to address these challenges. More importantly, it emphasizes the crucial role of model selection and tuning in predictive analytics, making the audience realize the significance and impact of their work. Compared to previous studies, the use of SMOTE and advanced hyperparameter tuning techniques like Keras Tuner provided a more balanced approach to handling class imbalance, albeit with room for improvement. The findings are consistent with existing research that emphasizes the difficulty of achieving high precision and recall simultaneously in imbalanced datasets. Unexpectedly, models with more layers and complex architectures, such as the seventh model, performed better in identifying job changers, suggesting that deeper models with appropriate regularization might capture more nuanced patterns. This study provides a framework for future research to further refine these approaches, underlining the importance of model selection and tuning in predictive analytics.

Recommendations for Practice

Based on the findings of this study, several recommendations can be made for theory and practice in predicting job change intentions within a food manufacturing company. First, practitioners should consider employing advanced hyperparameter tuning methods, such as Random Search CV and Grid Search CV, which demonstrated improved model performance in this study. These methods help optimize model parameters efficiently, leading to better overall accuracy. However, it is crucial to balance precision and recall, particularly for the minority class of job changers. As observed, models five and six that utilized these tuning methods showed significant promise in enhancing predictive capabilities.

Another critical recommendation is to address class imbalance using techniques like SMOTE, which was used in model eight. The application of SMOTE in this study resulted in a more balanced recall for job changers, underscoring its crucial role in managing class imbalances in predictive models. Organizations should integrate SMOTE or similar resampling techniques into their predictive modeling workflows to ensure that minority classes are adequately represented, thereby enhancing the reliability of predictions for job change intentions. This approach aligns with existing literature that emphasizes the importance of handling class imbalance to enhance the robustness of predictive models.

Lastly, it is recommended that practitioners incorporate deeper neural network architectures with appropriate regularization, as evidenced by the seventh model's performance. Using multiple dense layers with regularization techniques such as dropout helped capture complex patterns in the data, leading to better identification of job changers. While deeper models require more computational resources, their ability to detect subtle relationships in the data makes them valuable tools for predictive analytics in HR practices. However, practitioners should be cautious in understating the applicability of these findings, as the specific context and characteristics of the food manufacturing industry may influence model performance. Future studies should explore and validate these models across organizational contexts to establish their generalizability.

Recommendations for Future Research

Based on the findings and implications of this study, future researchers should explore several avenues to build upon and enhance the understanding of predicting job change intentions within the food manufacturing industry. One area for future research is examining additional features influencing job change decisions. For instance, factors such as employee engagement, job satisfaction, and workplace culture could provide deeper insights into the predictors of job change intentions. Future studies can develop more nuanced and accurate predictive models by incorporating a more comprehensive set of features. Additionally, researchers should consider conducting longitudinal studies to understand how job change intentions evolve, which further enriches these models' predictive power and applicability.

To improve upon this study, future researchers should address its limitations by increasing the sample size and diversity of the dataset. This study utilized a specific dataset from a single food manufacturing company, which may limit the generalizability of the findings. Future studies should aim to collect data from multiple companies across different geographical locations within the food manufacturing industry. This approach would help validate the models and ensure their broader applicability. Moreover, researchers should explore advanced machine learning techniques, such as ensemble methods, which can combine multiple models to achieve better performance and robustness. Techniques like boosting and stacking could be particularly beneficial in refining predictions and handling complex patterns in the data.

The next logical step in this line of research is to integrate real-time data analytics into the predictive modeling framework. With the rise of big data and IoT (Internet of Things) technologies, companies can collect and analyze real-time data on employee behavior and job performance. Future researchers should develop models to process and interpret this real-time data, providing organizations with timely and actionable insights to address job change intentions proactively. Additionally, exploring the integration of explainable AI (XAI) techniques will be crucial to ensure that the predictive models are transparent and that HR professionals can easily understand their decisions. That would improve trust in the models and facilitate more effective organizational decision-making processes.

Conclusions

This study used advanced deep learning techniques to predict job change intentions within a food manufacturing company. By addressing the problem of employee attrition, the study aimed to provide valuable insights into the factors influencing employees' decisions to change jobs and develop predictive models to assist HR professionals in proactive talent management. The importance of this study lies in its potential to improve employee retention strategies, reduce job change intention costs, and enhance overall organizational efficiency.

The key takeaway from this study is the practical value of predictive models, particularly those employing deep learning techniques, in forecasting job change intentions. Among the eight models evaluated, the integration of SMOTE for handling class imbalance and Keras Tuner for hyperparameter optimization emerged as the most effective approaches. This model struck the best balance between accuracy and the ability to correctly identify employees likely to consider a job change. The findings underscore the practical utility of advanced predictive analytics in enhancing HR decision-making processes and aligning retention strategies with data-driven insights.

Unlike previous research, this study builds on existing theories of employee job change intention and incorporates advanced deep learning models. While traditional studies have primarily focused on statistical analyses, this research demonstrates the advantages of deep learning models in capturing complex patterns within employee data. For applied studies, the results highlight the practical application of these models in real-world HR contexts, providing a robust framework for predicting job change intentions and informing strategic interventions. This advancement represents a significant step towards more sophisticated and effective talent management practices in the food manufacturing industry.

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