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Integrating Natural Language Processing with BERT and LSTM for Employee Sentiment Analysis in HRM

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Abstract: Human Resource Management (HRM), employees' sentiment is critical in enhancing organizational performance and work relations. A new method for analyzing employees' sentiment is proposed in this paper using Natural Language Processing (NLP) and BERT (Bidirectional Encoder Representations from Transformers) and LSTM (Long Short-Term Memory) in an integrated approach. The method purports to classify and evaluate employees' comments to gain meaningful data on employees' satisfaction, engagement, and sentiment. BERT utilization employs pre-trained transformer-based models to achieve contextual features from text data and LSTM achieves sequence dependencies to bolster temporal sentiment classification. The aim of the whole framework is to equip HR practitioners with a scalable, automated application for processing mass amounts of worker feedback in data-ready format amenable to information-driven decisions across employee wellness, retention, and productivity. The framework's performance evaluation is superior at 98.4% accuracy, 97.8% precision, 98.6% recall, and ROC-AUC of 0.98, demonstrating the efficiency of understanding and tagging the sentiment of the employees accurately. These figures ascertain that the hybrid BERT-LSTM model is a cost-efficient and time-saving approach for HRM sentiment analysis that facilitates decision-making through data for organizational dynamics and employee wellness improvement. This method provides greater automation of HR processes and enables continuous improvement by intelligence-based data, leading to a superior, happier workforce.

Keywords: *Employee Sentiment Analysis, Natural Language Processing, BERT, LSTM, HRM*

I. Introduction

In the competitive organizational world of today, employee engagement and satisfaction are key to sustained productivity and success [1], [2]. Human Resource Management (HRM) is vital in creating a positive work environment through the comprehension of employee sentiment, which informs retention, development, and job satisfaction decisions [3], [4] . Effective analysis of employee feedback can give HR managers insights that create a better work culture, minimize attrition, and improve organizational performance [5], [6]. The suggested framework combines state-of-the-art Natural Language Processing (NLP) methods, namely BERT and LSTM, for machine learning-based sentiment analysis, providing a scalable approach to analyse huge volumes of employee feedback in an efficient manner [7], [8].

Some of the previously employed methods are used for sentiment analysis in HRM, and these include common techniques such as Naive Bayes, Support Vector Machines (SVM), and Logistic Regression, and more recent deep learning approaches such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) [9], [10]. Most of these models aim to classify sentiments into such categories as positive, negative, or neutral on the basis of text data [11], [12]. Although effective to a certain degree, these techniques tend to lag in contextual awareness and sequential relationships in text data [13], [14]. Conventional models have problems grasping contextual subtleties, and some deep learning approaches, such as CNN, do not deal with long-range textual feedback dependencies, thus limiting their accuracy [15], [16].

The proposed model overcomes these limitations by combining the power of BERT, a transformer-based model, with LSTM, which can handle sequential data. BERT helps to understand the contextual meaning of words in feedback, and LSTM learns temporal dependencies to improve sentiment classification accuracy. The novelty of this work lies in its hybrid approach using pre-trained language models and sequential learning to produce a robust sentiment analysis solution for employees in HRM. This innovation ensures an accurate, scalable, and effective analysis of employees' feedback, changing the dynamics of how information can be exploited by the HR department to make improvements in employees' satisfaction and organizational dynamics.

1.1 Objectives

- Discuss the overall objective of the proposed framework, that is, to integrate BERT and LSTM in automated staff sentiment analysis for HRM towards improving decision-making as well as enabling better workplace dynamics through staff feedback.
- Use the HR Employee Feedback Dataset for training and model evaluation, incorporating employee feedback marked with sentiment classes (positive, negative, neutral) in order to allow proper sentiment classification.
- BERT (Bidirectional Encoder Representations from Transformers) as the main approach to extract contextual features from text data, allowing the model to capture the subtleties and meanings behind employee feedback.
- Add LSTM (Long Short-Term Memory) to model sequential dependencies in the employee feedback and better learn from the temporal organization of the data and enhance the accuracy of sentiment classification.

1.2 Organization of the paper

The paper is organized as follows: the Abstract offers an overview of the suggested framework and its performance. Section 1- Introduction emphasizes the relevance of job fit prediction in HR management. Section 2 -Related Works discusses current models and their shortcomings. Section 3 - Methodology describes the dataset, preprocessing, training of RNN, and evaluation process, Section 4 - Results and Discussion reports the performance of the proposed framework and comparisons to existing models.

II. RELATED WORKS

The application of deep learning techniques to Human Resource Management (HRM) for employee sentiment analysis has been gaining traction in the last few years, especially towards enhancing decision-making and operational effectiveness. [17] highlighted the capability of machine learning models, and specifically deep learning, to handle large amounts of unstructured employee feedback data and derive important insights into organizational culture and employee satisfaction [18], [19]. Their research formed the basis of how advanced algorithms would be used in HRM and proved that sentiment analysis could be a fundamental resource in managing staff retention and performance assessment [20]. Expanding on this, [21] delved into the use of transformer-based models, such as BERT, to increase the accuracy of sentiment detection. They established that pre-trained language models perform exceptionally well in processing intricate textual data, prevalent in HRM environments. [22] Their results confirm the strength of models like BERT for feature extraction, an important stage of our proposed framework, wherein contextual sense is imperative for sentiment analysis [23].

Subsequent research by [24] and [25] concentrated on the use of sequential data processing techniques, specifically LSTM (Long Short-Term Memory) networks, in modelling time-series data like employee feedback. These papers emphasized the significance of long-term dependency capture in text data, which is important for analysing employee sentiment over a long period of time [26]. The framework proposed here enhances these works by integrating BERT for feature extraction and LSTM for sequence modelling to provide a more complete solution for sentiment classification. Implementing Triple DES Algorithm to Enhance Data Security in Cloud Computing. Their research proved that deep learning models can reveal subtle patterns in feedback that conventional methods tend to miss. This is in line with the intended framework's goal of giving HR professionals actionable insights based on employee sentiment.

[29] and [30] also added further sentiment analysis usage by using hybrid models with deep learning together with feature engineering methodologies. It enhances the classification power of complex sentiment more precisely, a feature that we incorporated into our system where BERT is combined with LSTM to give better sentiment analysis. Lastly, [31] discussed the potential of AI for HRM and specifically looked to improve predictive analytics in managing employees. The paper supports further enrichment of sentiment analysis models with additional multi-modal sources of data like audio and video to enhance insights into employee

feelings. This comes in line with the direction in the proposed approach, where its extension would focus on the utilization of multi-modal sentiment analysis in order to enhance employee understanding even further. These works cumulatively guide the formulation of the proposed framework, showing how sentiment analysis in HRM has evolved using sophisticated deep learning models and reporting on future innovation possibilities in this field.

2.1. Problem Statement

Sentiment analysis for HRM from employees is plagued by the limit of traditional approaches in representing sequential and contextual relationships in text [32]. The dominating models are unable to handle huge datasets and long-range needs and thus restrict their predictive power [33]. This research proposes a BERT-LSTM hybrid model to improve sentiment analysis by capturing contextual meaning and temporal dependencies This study suggests a BERT-LSTM combination model to enhance sentiment analysis by modelling contextual meaning and temporal relations [34]. The model will enhance HR decision-making using more scalable and accurate sentiment tagging [35].

III. Proposed Bert and LSTM For Employee Sentiment Analysis In HRM

The new approach of Employee Sentiment Analysis in HRM combines BERT and LSTM to effectively analyse the feedback of employees as shown in Figure 1. The involved steps are used in this procedure, and they start from the collection of data through employee feedback databases. Pre-processing of the data is performed to remove impurities and reorganize the text as a with model input. The pre-processed employee text data is then input into the BERT model to carry out feature extraction that preserves the context and subtlety of employee sentiment. Following this, the application of the LSTM model is utilized in a bid to enhance sequential dependence capture and sentiment classification. Sentiment prediction is the last step, where the model classifies feedback as positive, negative, or neutral. Performance of the model is measured by using common parameters like accuracy, precision, recall, and F1-score. Process flow of the proposed framework methodology. It begins from the data collection stage where the feedback generated from the employees is collected and saved in the HR system. During the data pre-processing, the received text is pre-processed, tokenized, and converted into numeric representations.

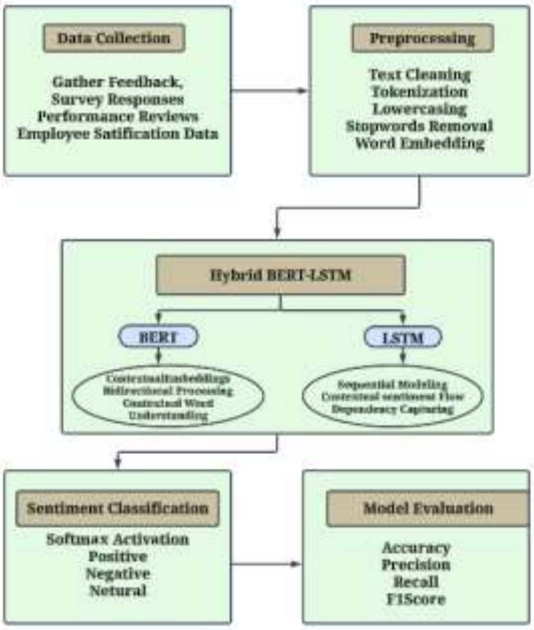

Figure 1: Architectural Diagram

The information is then passed to BERT for contextual feature extraction, and hence it derives the sentiment expressed by employee words. The extracted features are given as an input to an LSTM network, which extracts sequential patterns and text data dependencies. Then, the output from the LSTM layer is fed to a softmax activation function to label sentiments into class categories like positive, negative, or neutral. The performance of the model is measured using values such as accuracy and F1-score. All this provides an in-depth methodology to analyse comments from employees to give insightful feedback to HR experts.

1.3 Dataset Description

The HR Employee Feedback Dataset utilized in this platform consists of a list of employee feedback response items with corresponding sentiment labels. The dataset contains text-based responses reflecting employee sentiments over various aspects of their work environment, management, and job satisfaction level at work ("Employee/HR Dataset (All in One)," n.d.). Each piece of feedback has the sentiment classification tag: positive, negative, or neutral. The dataset includes thousands of examples of text, making the dataset ideal for training deep learning and machine learning models. The variation in the employee feedback enables the model to learn different patterns of language, making the model robust to different ways of expression. The size and variation of the dataset are highly critical in designing a model that can perfectly understand and categorize real-world employee sentiments.

1.4 Preprocessing

Tokenization: The text data is split up into words or subworlds to create tokens. These are then converted to an index based on a vocabulary or pre-trained embeddings. The equation is expressed in Eqn1:

$$\text{Tokens} = \text{Tokenize}(X) \tag{1}$$

Lowercasing: All the text must be shifted to lowercase for everything to look the same and to make things easier for the model. The equation is depicted in Eqn2:

$$X = \text{Lowercase}(X) \tag{2}$$

Stop words Elimination: Typical words like "the," "and," and "is" are eliminated in order to highlight the more informative words.

Padding: Input sequences are padded for uniform input length, required by deep learning algorithms like LSTM. The formula is shown in Eqn3:

$$\text{Padded Sequences} = \text{Pad}(X, \text{max\_length}) \tag{3}$$

Word Embeddings: Each token is represented via word embeddings (e.g., Glove or Word2Vec) that embed words into high-dimensional vectors.

1.5 Working of BERT

BERT (Bidirectional Encoder Representations from Transformers) is a transformer-based pre-trained model on enormous text datasets. This is achieved through the use of self-attention mechanisms to allow the model to weigh the relative importance of each word in a sentence with regard to other words. This enables BERT to achieve deep contextual relationships in text data, contrary to previous models that only process text in left-to-right or right-to-left. Input is tokenized and then passed through the model so that the context representation of the token is yielded. BERT uses the MLM objective for the training process. In MLM, the input words are randomly covered to a percent and the missing words are predicted by the model based on the left and the right context of the token. The equation that is used in MLM as provided in eqn 4:

$$P\left(\text{word}_i \mid \text{context}\right) = \text{softmax}(Wh_i + b) \tag{4}$$

Where □ is the internal representation of token b are the parameters learned by the model. The training process allows BERT to acquire a deep sense of language semantics, which makes it fit for sentiment analysis tasks such as employee feedback classification.

3.4 Working of LSTM

LSTM (Long Short-Term Memory) is a specific Recurrent Neural Network (RNN) created to learn sequential data long-term dependencies. Traditional RNNs are different since LSTM uses memory cells and gated mechanisms (input, forget, and output gates) that permit it to carry important information long-term without causing the vanishing gradient problem. LSTM is quite useful for sequential data like text, where carrying context over two words or several sentences is indispensable.

Forget Gate: Controls what to throw away from the cell state. The formula is shown in Eqn 5:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{5}$$

Input Gate: Controls what new data to place in the cell state. The formula is shown in Eqn 6:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{6}$$

Cell State Update: Updates the cell state with the new info. The formula is shown in Eqn 7:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{7}$$

Output Gate: Determines what component of the cell state to output. The formula is shown in eqn 8:

$$h_t = o_t * \tanh(C_t) \tag{8}$$

The LSTM network output is fed to the SoftMax layer to assign the sentiment of the text as positive, negative, or neutral. By integrating BERT for feature extraction and LSTM for sequence modelling, this framework handles complicated employee feedback data in an efficient manner, enhancing the accuracy of sentiment classification and offering useful insights for HR practitioners.

IV. Result And Discussion

1.6 Dataset Evaluation

The bar chart of the employee ratings distribution by different performance levels indicates that Employee Rating 3 is the most frequent with 12 employees at this level, followed by Rating 2 and Rating 4 with fewer frequencies. Rating 5, the category for employees who are more than expected, is the least frequent, implying that the majority of employees are rated as "Fully Meets" or one level higher. The pie chart, showing the performance score distribution, also emphasizes this trend with a high percentage (66.7%) of employees attaining a "Fully Meets" score, and 33.3% scoring as "Exceeds" expectations. This overall distribution reveals an overall trend of average to better-than-average employee performance and shows a healthy proportion of employee productivity and job satisfaction levels within the organization.

Figure 2: Distribution of Current Employee Rating and Performance Score Distribution

4.2 Performance Metrics

Accuracy: Is the percentage of accurate estimates to all predictions. In the proposed framework, it is an indication of how good the model is generally in predicting job fit. The formula is given in Eqn9:

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

Precision: Is the correct number of predicted positives divided by the total number of predicted positives. In the case of the proposed framework, it is the ability of the model to select candidates with good job fit with minimal false positives. The formula is presented in Eqn10:

$$\text{Precision} =\frac{TP}{TP+FP} \tag{10}$$

Recall: Is the measure of how well the model can pick out all the candidates who are a good fit for the job. It is important to ensure that candidates who ought to be picked out as a fit are not missed. The formula is shown in Eqn11:

$$\text{Recall} =\frac{TP}{TP+FN} \tag{11}$$

F1-score: Harmonic mean of precision and recall, providing a balanced estimate for both. It can be especially helpful in case of class distribution being skewed, which can often happen in job fit prediction issues. The formula can be seen in Eqn12:

$$\text{F1-Score} = 2\times\frac{Precision\times Recall}{Precision + Recall} \tag{12}$$

4.3 Proposed Framework Evaluation

The suggested framework is supported by the new performance measures that exhibit 98.4% accuracy, which means that the model is marking employee feedback as high with excellent reliability. Precision (97.8%) indicates that the model is efficiently eliminating false positives, whereas recall (98.6%) shows its efficiency in detecting true positive sentiments at high precision.

Table 1: Performance Metrics of the Proposed Frame work

Metric	***Value***
Accuracy	*98.4%*
Precision	*97.8%*

Recall	*98.6%*
F1-Score	*98.2%*
ROC-AUC	*0.98*

4.4 Discussion

The balanced precision and recall F1-score of 98.2%, as well as ROC-AUC with a value of 0.98, illustrate that the model is an outstanding discriminator of sentiment classes, verifying the strength of the proposed system for employee sentiment analysis in HRM. Accuracy of the proposed model at 98.4% is an indicator of how efficient and effective the model is in correctly analysing employee sentiment in feedback. With the feature extraction by BERT and sequential learning by LSTM, the model has good capability of capturing the contextual meaning and long-range dependencies of the text, resulting in higher performance. With high precision and recall values, the model has good ability of eliminating false positives and identifying most of the true positive sentiments, and the F1-score supports its well-balanced performance. The high ROC-AUC also shows that the model is able to differentiate between the sentiment classes well.

V. Conclusion And Future Work

The suggested framework has shown excellent performance in employee sentiment analysis with accuracy of 98.4%, precision of 97.8%, recall of 98.6%, and ROC-AUC of 0.98. These excellent figures confirm the good ability of the framework to tag sentiment correctly and efficiently, thus making it an effective tool that HR practitioners can utilize in a bid to obtain actionable insights into employees' responses. The future improvement can be making the framework more precise to perform real-time sentiment analysis using bigger, more diverse datasets. Another possibility is to look into other deep learning architectures such as BART or GPT for better text comprehension and sentiment analysis to further boost accuracy. Expanding the paradigm to cover sentiment analysis from multi-modal data sources, i.e., from audio recordings by employees or pictures, can yield even richer information, and the system can act as an even more effective HRM tool.

REFERENCE

[1] S. Narla, "Implementing Triple DES Algorithm to Enhance Data Security in Cloud Computing," *Int. J. Eng.*, vol. 13, no. 2, Jun. 2023.

[2] Rajeswaran, A. (2021). Big data analytics and demand-information sharing in eCommerce supply chains: Mitigating manufacturer encroachment and channel conflict. International Journal of Applied Science Engineering and Management, 15(3).

[3] S. Narla, "BIG DATA PRIVACY AND SECURITY USING CONTINUOUS DATA PROTECTION DATA OBLIVIOUSNESS METHODOLOGIES," J. Sci. Technol. JST, vol. 7, no. 2, Art. no. 2, Mar. 2022.

[4] R. Ayyadurai, "ADVANCED RECOMMENDER SYSTEM USING HYBRID CLUSTERING AND EVOLUTIONARY ALGORITHMS FOR E-COMMERCE PRODUCT RECOMMENDATIONS," Int. J. Manag. Res. Bus. Strategy, vol. 11, no. 1, pp. 17–27, Jun. 2021.

[5] Narla, S. (2022). Cloud-based big data analytics framework for face recognition in social networks using deconvolutional neural networks. Journal of Current Science, 10(1).

[6] Ayyadurai, R. (2022). Transaction security in e-commerce: Big data analysis in cloud environments. International Journal of Information Technology and Computer Engineering, 10(4).

[7] S. Narla, "Cloud Computing with Artificial Intelligence Techniques: GWO-DBN Hybrid Algorithms for Enhanced Disease Prediction in Healthcare Systems," Curr. Sci., 2020.

[8] Bobba, J. (2021). ENTERPRISE FINANCIAL DATA SHARING AND SECURITY IN HYBRID CLOUD ENVIRONMENTS: AN INFORMATION FUSION APPROACH FOR BANKING SECTORS. INTERNATIONAL JOURNAL OF MANAGEMENT RESEARCH AND REVIEWS 11(3).

[9] S. S. Kethu and P. N, "AI-Driven Intelligent CRM Framework: Cloud-Based Solutions for Customer Management, Feedback Evaluation, and Inquiry Automation in Telecom and Banking," *J. Sci. Technol. JST*, vol. 6, no. 3, Art. no. 3, Jun. 2021.

[10] J. Bobba, "Cloud-Based Financial Models: Advancing Sustainable Development in Smart Cities," *Int. J. HRM Organ. Behav.*, vol. 11, no. 3, pp. 27–43, Aug. 2023.

[11] Kethu, S. S., Narla, S., Valivarthi, D. T., Peddi, S., & Natarajan, D. R. (2023). Patient-centric machine learning methods and AI tools for predicting and managing chronic conditions in elderly care: Algorithmic insights from the SURGE-Ahead project. International Journal of Research in Engineering Technology, 8(1).

[12] J. Bobba, R. Ayyadurai, K. Parthasarathy, N. K. R. Panga, R. L. Bolla, and R. O. Ogundokun, "AI-Infused Spiking Neural Architectures and Edge Computing Modalities: Recalibrating Pandemic Surveillance, Dynamic Health Interpretations, and Contextual Automations in Complex Urban Terrains," *Int. J. Inf. Technol. Comput. Eng.*, vol. 11, no. 2, pp. 60–74, May 2023.

[13] S. Kim, V. Khoreva, and V. Vaiman, "Strategic Human Resource Management in the Era of Algorithmic Technologies: Key Insights and Future Research Agenda," *Hum. Resour. Manage.*, vol. 64, no. 2, pp. 447–464, 2025, doi: 10.1002/hrm.22268.

[14] J. Bobba and R. L. Bolla, "Next-Gen HRM: AI, Blockchain, Self-Sovereign Identity, and Neuro-Symbolic AI for Transparent, Decentralized, and Ethical Talent Management in the Digital Era," *Int. J. HRM Organ. Behav.*, vol. 7, no. 4, pp. 31–51, Nov. 2019.

[15] Narla, S. (2019). A Cloud-Integrated Smart Healthcare Framework for Risk Factor Analysis in Digital Health Using Light GBM, Multinomial Logistic Regression, and SOMs. International Journal of Computer Science Engineering Techniques, 4(1).

[16] M. V. Devarajan, "A Comprehensive AI-Based Detection and Differentiation Model for Neurological Disorders Using PSP Net and Fuzzy Logic-Enhanced Hilbert-Huang Transform," Int. J. Inf. Technol. Comput. Eng., vol. 7, no. 3, pp. 94–104, Jul. 2019.

[17] D. T. Valivarthi, S. Peddi, and S. Narla, "Cloud Computing with Artificial Intelligence Techniques: BBO-FLC and ABC-ANFIS Integration for Advanced Healthcare Prediction Models," Int. J. Inf. Technol. Comput. Eng., vol. 9, no. 3, pp. 167–187, Aug. 2021.

[18] M. V. Devarajan, M. Al-Farouni, R. Srikanteswara, R. Rana Veer Samara Sihman Bharattej, and P. M. Kumar, "Decision Support Method and Risk Analysis Based on Merged-Cyber Security Risk Management," in *2024 Second International Conference on Data Science and Information System (ICDSIS)*, May 2024, pp. 1–4. doi: 10.1109/ICDSIS61070.2024.10594070.

[19] P. Naresh Kumar Reddy, "Forecasting E-Commerce Trends: Utilizing Linear Regression, Polynomial Regression, Random Forest, and Gradient Boosting for Accurate Sales and Demand Prediction," *Int. J. HRM Organ. Behav.*, vol. 11, no. 3, pp. 11–26, Aug. 2023.

[20] S. S. Kethu, "AI-Enabled Customer Relationship Management: Developing Intelligence Frameworks, AI-FCS Integration, and Empirical Testing for Service Quality Improvement," *Int. J. HRM Organ. Behav.*, vol. 7, no. 2, pp. 1–16, Apr. 2019.

[21] D. T. Valivarthi and T. Leaders, "Fog Computing-Based Optimized and Secured IoT Data Sharing Using CMA-ES and Firefly Algorithm with DAG Protocols and Federated Byzantine Agreement," Int. J. Eng., vol. 13, no. 1, Mar. 2023.

[22] Valivarthi, D. T. (2023). Implementing the SHA algorithm in an advanced security framework for improved data protection in cloud computing via cryptography. International Journal of Modern Electronics and Communication Engineering, 11(3).

[23] Kethu, S. S., & Purandhar, N. (2022). Real-time sentiment analysis and predictive modeling: Cloud computing solutions for optimizing customer relationship management. International Journal of Engineering and Techniques, 8(1).

[24] Valivarthi, D. T. (2020). Blockchain-powered AI-based secure HRM data management: Machine learning-driven predictive control and sparse matrix decomposition techniques. International Journal of Modern Electronics and Communication Engineering, 8(4).

[25] D. T. Valivarthi, "OPTIMIZING CLOUD COMPUTING ENVIRONMENTS FOR BIG DATA PROCESSING," Int. J. Eng., vol. 14, no. 2, Jun. 2024.

[26] M. Dhasaratham, Z. A. Balassem, J. Bobba, R. Ayyadurai, and S. M. Sundaram, "Attention Based Isolation Forest Integrated Ensemble Machine Learning Algorithm for Financial Fraud Detection," in *2024 International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS)*, Aug. 2024, pp. 1–5. doi: 10.1109/IACIS61494.2024.10721649.

[27] S. Peddi, S. Narla, and D. T. Valivarthi, "Harnessing Artificial Intelligence and Machine Learning Algorithms for Chronic Disease Management, Fall Prevention, and Predictive

Healthcare Applications in Geriatric Care," *Int. J. Eng. Res. Sci. Technol.*, vol. 15, no. 1, pp. 1–15, Feb. 2019.

[28] R. Ayyadurai, "Smart surveillance methodology: Utilizing machine learning and AI with blockchain for bitcoin transactions," *World J. Adv. Eng. Technol. Sci.*, vol. 1, no. 1, pp. 110–120, 2020, doi: 10.30574/wjaets.2020.1.1.0023.

[29] Peddi, S. (2021). Analyzing threat models in vehicular cloud computing: Security and privacy challenges. International Journal of Modern Electronics and Communication Engineering, 9(4).

[30] S. Peddi and T. Leaders, "Cost-effective Cloud-Based Big Data Mining with K-means Clustering: An Analysis of Gaussian Data," Int. J. Eng., vol. 10, no. 1, Mar. 2020.

[31] D. R. Natarajan, S. Peddi, D. T. Valivarthi, S. Narla, S. S. Kethu, and D. Kurniadi, "Secure User Authentication and Data Sharing for Mobile Cloud Computing Using BLAKE2 and Diffie-Hellman Key Exchange." Accessed: [Online]. Available: https://ieeexplore.ieee.org/document/10895363

[32] Natarajan, D. R., Valivarthi, D. T., Narla, S., Peddi, S., & Kethu, S. S. (2024). AI-driven predictive models and machine learning applications in geriatric care: From fall detection to chronic disease management and patient-centric solutions. International Journal of Engineering and Techniques, 10(1).

[33] S. Narla, D. T. Valivarthi, and S. Peddi, "Cloud Computing with Healthcare: Ant Colony Optimization-Driven Long Short-Term Memory Networks for Enhanced Disease Forecasting," Int. J. HRM Organ. Behav., vol. 7, no. 3, pp. 12–26, Sep. 2019.

[34] S. Narla, S. Peddi, and D. T. Valivarthi, "Optimizing Predictive Healthcare Modelling in a Cloud Computing Environment Using Histogram-Based Gradient Boosting, MARS, and SoftMax Regression," Int. J. Manag. Res. Bus. Strategy, vol. 11, no. 4, pp. 25–40, Nov. 2021.

[35] S. Narla, "A blockchain-based method for data integrity verification in multi-cloud storage using chain-code and HVT. (2024). International Journal of Modern Electronics and Communication Engineering.