Vol. 3 No. 3 (2025)

Spectrum of Engineering Sciences

SPECTRUM OF ENGINEERING SCIENCES

Online ISSN 3007-3138

Print ISSN 3007-312X

A Deep Learning-Based Enhanced Sentiment Classification and Consistency Analysis of Queries and Results in Search Using Oracle Hybrid Feature Extraction

Muhammad Yousaf[1*]
Department of Computer Science, Faculty of Computer Science & IT Superior, University Lahore, 54000, Pakistan.
Corresponding Author Email: su92-mscsw-f24-005@superior.edu.pk

Farwa Khalid[2]
University of Narowal, Narowal. farvaanvar@gmail.com

Muhammad Usman Saleem[3]
Department of Computer Science, Government College Women University, Sialkot. usman.saleem@gcwus.edu.pk & usman.saleem@live.com

Mohe Ud Din[4]
Department of Computer Science, Faculty of Computer Science& IT Superior, University Lahore, 54000, Pakistan
sheikhgmd60@gmail.com

Abdul Karim Shahid[5]
Computer Science Department, COMSATS University Islamabad, Lahore Campus. akarim@cuilahore.edu.pk

Hamayun Khan[6]
Department of Computer Science, Faculty of Computer Science & IT Superior, University Lahore, 54000, Pakistan
hamayun.khan@superior.edu.pk

Abstract

Multiple assessments of customer feedback play a vital role in the industry because they help enhance product quality while spotting major network issues and creating improved customer-facing services. A traditional sentiment analysis process relies on external machine learning frameworks that result in system integration issues and performance reduction because large data volumes transfer between different options such as API and FTP file sharing before applying data machine learning

Vol. 3 No. 3 (2025)

Spectrum of Engineering Sciences

Online ISSN

3007-3138

Print ISSN

3007-312X

SPECTRUM OF ENGINEERING SCIENCES

models that extract insights. This paper proposed a Machine learning-based Model based on (CNN, RNN, and DT Classifier) and focuses on extracting sentiment metadata that links to the user-selected topic or entity together with their search results. The real-time sentiment analysis system which operates in Oracle Autonomous Database uses OML4SQL and OML4PY components from Oracle Machine Learning to process Communication customer feedback obtained through the web-based Oracle APEX system. The predictive model developed by the research utilizes CNNs and RNN algorithms provided by Oracle to identify whether customer reviews are positive, negative, or neutral. After receiving training the model functions to classify fresh feedback immediately while bypassing dependencies on external AI platforms. The implementation occurs inside the Autonomous Oracle Database while bypassing API or FTP file-sharing methods. The analysis reveals OML4SQL and OML4PY succeed in customer sentiment analysis thus enabling Software organizations to acquire valuable business information for better service delivery and strategic choices. The findings from this research demonstrate that the Convolutional Neural Network (CNN) achieved the highest accuracy (92.5%), followed by RNN (90.2%), while DT (85.4%) performed relatively lower. The analysis of 15,500 customer reviews revealed that 48.1% were positive, 39.4% were negative, and 33.7% were neutral. Oracle machine learning tools (ML4SQL and OML4PY) provide real-time text analytics in Software databases which enables service-based decisions through automated sentiment analysis technology within customer support operations.

Keywords: Sentiment Analysis, Oracle Machine Learning for SQL (OML4SQL), Oracle Machine Learning for Python (OML4PY), Machine Learning.

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

Introduction

The extensive use of connected devices created outstanding connectivity opportunities while simultaneously opening new possibilities for harmful activity. The methods used at present for cyber attack detection serve to block harmful network connections so defense teams can analyze attack scenarios [1, 2]. Facebook operates as the leading social network for human interaction since it maintains over 2.27 billion active users worldwide. Facebook users communicate through its features to exchange thoughts in public and private conversations with community members in modern-day social environments. As a part of their operations Software companies gather numerous customer feedback submissions from their web-based Oracle APEX feedback forms. The evaluation process requires automated sentiment classification solutions because analyzing data manually proves inefficient and time-consuming [3, 4].

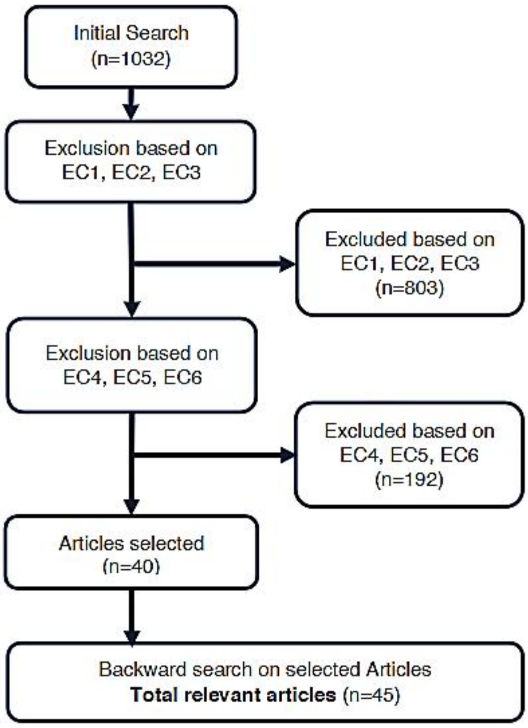

Figure 1: Systematic Procedure for Literature

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

Currently available research focuses on sentiment analysis in retail markets and healthcare as well as financial domains yet it lacks studies about Software customer feedback evaluation. Software firms acquire extensive amounts of unorganized customer feedback from surveys alongside phone calls and digital platforms [5, 6].

Modeling Oracle Unavailability

This feedback cannot be processed manually thus automated sentiment classification proves to be essential. Research about implementing sentiment analysis through ML remains scarce when applied to enterprise-level database systems that use Oracle as their main platform [7, 8]. Existing sentiment analysis research faces a significant limitation because it depends on external machine learning tools according to the report [9]. Real-time sentiment classification becomes challenging because these frameworks force users to extract data from databases before external model training followed by result import. Security and scalability issues along with performance considerations are resolved through Oracle Machine Learning (ML4SQL and OML4PY) which performs its machine learning capabilities inside the database system without data transfers to external programs. Current scholarly investigation about conducting sentiment analysis directly inside Oracle's information system remains limited [10, 11]. The study deals with this void through the development of real-time sentiment analysis models based on Oracle Machine Learning (ML4SQL and OML4PY) which incorporates its CNN and RNN classifiers. The direct implementation of analysis within the oracle autonomous database ensures integration independence and fast processing while maintaining improved security measures [12, 13].

Spectrum of Engineering Sciences
Online ISSN
3007-3138
SPECTRUM OF ENGINEERING SCIENCES
Print ISSN
3007-312X

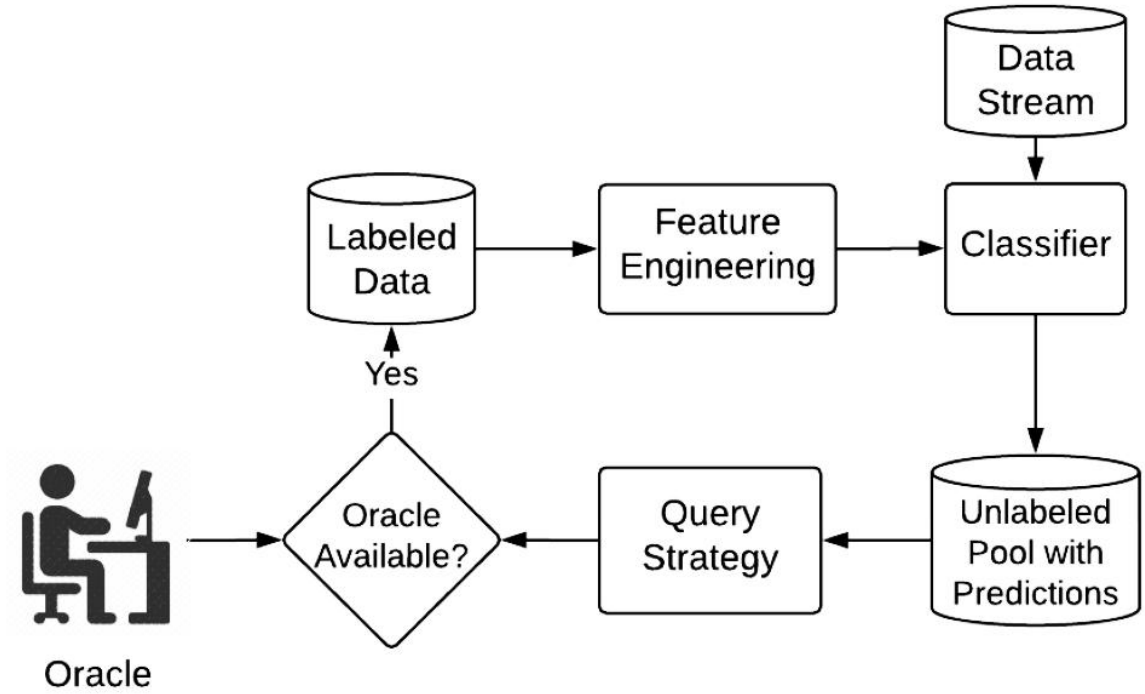

Figure 2: Generic Oracle Framework for Prediction [14]

Related Work

The model functions through supervised learning after using trained labeled information from customers to analyze new feedback sentiment. A feedback repository known as a table exists in an Oracle database to store information that serves upcoming processes. The results from this study will create improved automated customer feedback analysis systems for Software organizations by implementing data-driven methods for enhancing business decisions and customer satisfaction [15]. They face the main barrier of merging their detection models into their current database framework while maintaining high performance and security levels. The research establishes a live sentiment analysis framework based on Oracle Machine Learning (ML4SQL and OML4PY) which helps Software sectors to automatically sort customer reviews into positive negative and neutral categories [16, 17]. Workers provide sentiment classifications (positive, negative, neutral) to specific data records which serve as training data for the machine learning system. The trained model analyzes new feedback automatically after obtaining

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X
unlabeled data through prediction. Stratified random sampling techniques are used to maintain equal splits between positive and negative feedback along with neutral expressions in the researched dataset [18-21]. The method ensures model accuracy by reducing systematic preference toward a specific sentiment category. The database contains at least 11409 feedback elements that are split into 40% positive/negative ratings alongside 20% neutral feedback. A database object called a table stores the feedback back for additional processes under the Oracle database term. The study results will advance automated customer feedback evaluation within Software companies through data-driven methods that improve both customer satisfaction and business choices [22, 23]. The main obstacle in this integration project involves performing this seamless integration of machine learning models into their existing database infrastructure without affecting performance or security standards. Businesses need to solve the primary obstacle of implementing machine learning models into their established database systems without sacrificing either performance or security measures.

Query Strategies in Oracle Machine Learning (ML4SQL and OML4PY)

The study solves this problem through the development of real-time sentiment analysis models using Oracle Machine Learning (ML4SQL and OML4PY) which helps Software businesses to automate feedback categorization into positive, negative, or neutral sections [24-28]. A small part of the database undergoes human handling to obtain positive, negative, and neutral sentiments which will serve as training data for the machine learning system. The prediction system uses automatic classification of new feedback through the trained model. Stratified random sampling enables the study to achieve an equal proportion of positive negative and neutral feedback. The distribution method guards against sentiment category preference which results in enhanced model

Spectrum of Engineering Sciences
Online ISSN
3007-3138
Print ISSN
3007-312X
SPECTRUM OF ENGINEERING SCIENCES

performance. The research data contains at least 11409 feedback entries distributed into 40% positive and negative and 20% neutral ratings. The research uses structured data analysis techniques to develop and test the sentiment classification capabilities of Oracle Machine Learning (ML4SQL and OML4PY) [29, 30]. Among the methods that analyze customer feedback data is a supervised learning model that detects positive, negative, and neutral customer sentiment. The study employs both ML4SQL and OML4PY systems within Oracle Machine Learning to detect which algorithm performs best for sentiment analysis [31]. After finishing training the model becomes deployed for analyzing new customer feedback. The comparison of sentiments over time enables organizations to detect patterns in customer satisfaction. Sentiment analytics data presented through Oracle Machine Learning for SQL graphs allows Software companies to enhance their services based on these results [32, 33]. New data results become available to decision-makers after training completion since these stakeholders do not show interest in training datasets. The deployed sentiment model enables real-time classification of live customer feedback for the company to identify service problems promptly and enhance their customer engagement methods using sentiment analysis findings. To conduct sentiment-based feedback analysis properly one must follow responsible data-handling practices for user information.

All ethical standards regarding privacy protection and fairness along with responsible AI utilization need to be followed. This study must adhere to the following fundamental ethical principles [34, 35]. Personal information gets detected within feedback submitted through Oracle APEX web pages. The study assures data privacy through the procedure of removing identity-correcting personal information like names phone numbers and email addresses. The system allows access to

Vol. 3 No. 3 (2025)

Spectrum of Engineering Sciences

Online ISSN

3007-3138

Print ISSN

3007-312X

SPECTRUM OF ENGINEERING SCIENCES

authorized staff members who respect strict security measures for data protection [36 37].

Method & Data Materials

The quantitative evaluation method proves suitable because text feedback from customers can be transformed into numerical representations which enables statistical content analysis. The systematic application of machine learning features in Oracle machine learning enables this research to conduct an objective classification process for customer sentiment assessment at scale. The framework of Oracle Machine Learning (ML4SQL and OML4PY) provides a built-in Oracle Database connection to enable users to build training and execution machine learning models through Oracle machine learning. The supervised machine learning model in ML4SQL and OML4PY performs sentiment classification where it determines feedback to be positive negative or neutral using historical data records. Automatic sentiment prediction for new data happens by using machine learning algorithms under quantitative approaches instead of manual qualitative text interpretation. All sensitive customer data stays protected within the secure database server to prevent unauthorized users from gaining access to it. The input feature vector processes through s^((b,t)) as per the below Eq (1). The proposed classifier contains i to represent random units of b-layer units and y to represent the total b-layer units.

$$S_i^{(b,t)} = \sum_{z=1}^{E} p_{iz}^{(b)} J_z^{(b-1,t)} + \sum_{i'}^{y} x_{ii'}^{(b)} J_{i'}^{(b,t-1)} \quad \text{Eq (1)}$$

$$J_i^{(b,t)} = \beta^{(b)}(S_i^{(b,t)}) \quad \text{Eq (2)}$$

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

$$P(w) = \sqrt{\frac{t}{f(w)} + \frac{t}{f(w)}},$$

Eq (3)

$$f(w) = \frac{count_w}{totalno.oftokens},$$

Eq (4)

Experiment Setup

The below-mentioned Figure 3 represents the proposed framework based on an autonomous Oracle database.

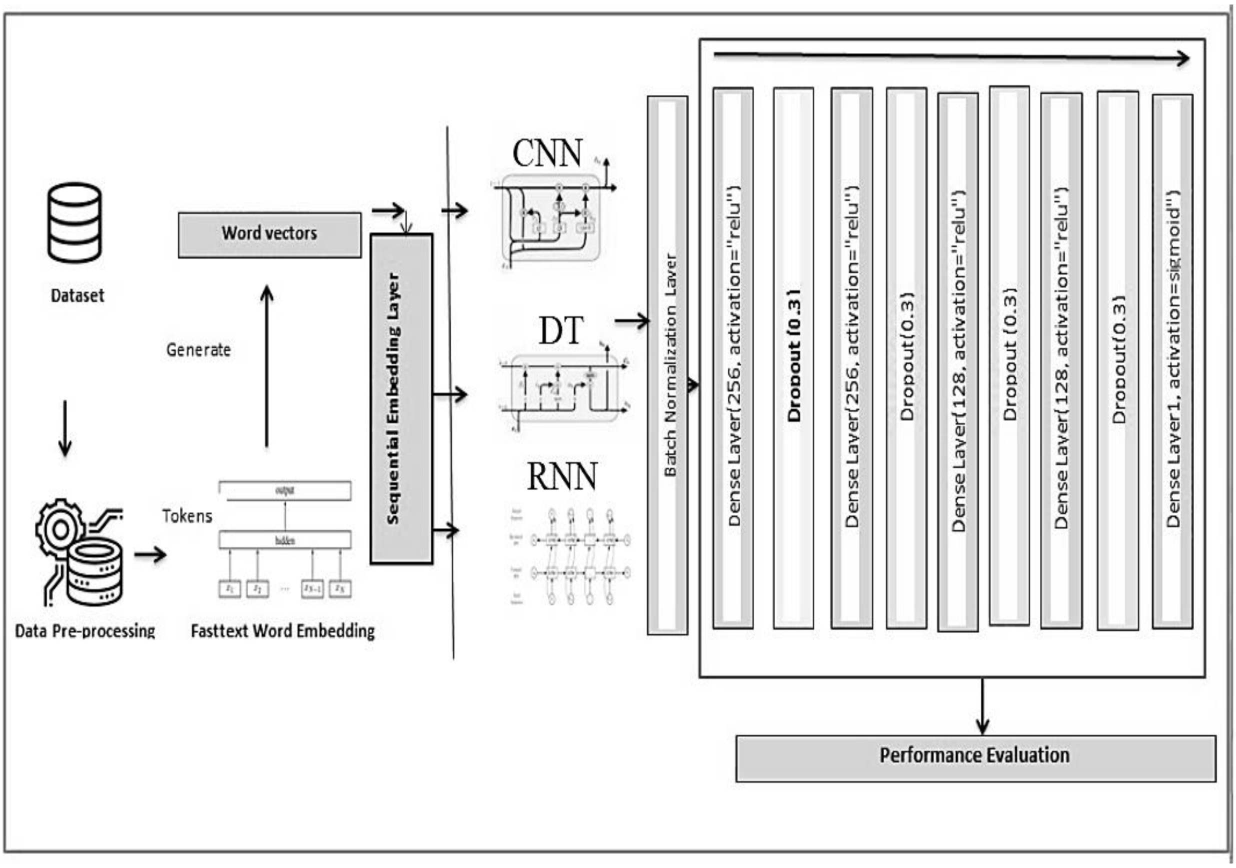

Figure 3: Proposed Framework

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

$$f_t = \sigma(W_f.[h_{(t-1)}, x_t] + b_f)$$
Eq (5)

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

Customers submit opinions, complaints, or appreciation through feedback forms available on the Software company's website and mobile app built in the Oracle APEX framework. This data includes free-text responses, which are later analyzed for sentiment classification. Once collected, the textual data undergoes preprocessing to remove noise and standardize content: Text Cleaning**:** Removal of special characters, HTML tags, and redundant spaces. The below-mentioned Figure 2 represents the OML4SQL extracts a single question-answer pair from unstructured text and separates it into two columns: "Question" and "Answer" using REGEXP_SUBSTR in Oracle SQL.

$$\tilde{C}_t = tanh(W_c.[h_{(t-1)}, x_t] + b_c),$$
Eq (7)

$$C_t = f_t * C_{(t-1)} + i_t * \tilde{C}_t,$$
Eq (8)

$$O_t = \sigma(W_O.[h_{(t-1)}, x_t] + b_o),$$
Eq (9)

The use of a dataset from the Oracle database table source leads to better sentiment model generalization capabilities. Real Customer feedback delivers information about actual service matters which lets this model work well for business implementations. The organized data sources establish an equilibrium between training data and evaluation requirements. These established data collection procedures help the

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

study create a complete collection of representative information which allows the development of a precise and scalable sentiment analysis model in Oracle Machine Learning (ML4SQL and OML4PY). The research relies on two data collection methods that include breaking the dataset into training and testing portions and implementing model training through sentiment-labeled data. A model optimization process of hyperparameter tuning works to maximize accuracy levels.

$$B = \{B_1, B_2, \ldots, B_k, \ldots, B_l\}$$ Eq (10)

$$E_c = \frac{1}{K} \times \sum_{g=1}^{k} J_v^{b,t} - k_v$$ Eq (11)

$$B_{m,n}(q+1)(1 - \frac{1 - X(0,1) - X(-1,1)}{1 - c_{m,n} \times f_{mn}(q)}) = X(0,1) \times R_{s,n}$$ Eq (12)

Evaluation Strategy and Evaluation Criteria

The results of the study provide a detailed analysis of customer sentiment based on feedback collected from a Software industry web page. The dataset consists of 11,409 customer reviews, which were classified into positive, negative, and neutral sentiments using Oracle Machine Learning (ML4SQL and OML4PY). The machine learning model classified the 11,409 customer reviews and stated that 46.8% of customer feedback was classified as positive, indicating overall customer satisfaction with Software services. 29.4% of feedback was negative, highlighting areas where service improvements are needed. 23.7% of responses were neutral, meaning customers neither expressed strong dissatisfaction nor satisfaction. To assess the performance of the sentiment analysis model, various metrics are used: Accuracy: Measures overall correctness of predictions.

Vol. 3 No. 3 (2025)

Spectrum of Engineering Sciences

Online ISSN 3007-3138

Print ISSN 3007-312X

SPECTRUM OF ENGINEERING SCIENCES

The accuracy is defined as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{Eq (11)}$$

Precision: Evaluate how many predicted positive/negative reviews were correct.

$$Precision = \frac{TP}{TP+FP} \quad \text{Eq (12)}$$

Recall measures the model's ability to identify the actual positive instances.

$$Recall = \frac{TP}{TP+FN} \quad \text{Eq (13)}$$

F1-Score: A balance between precision and recall.

$$F1 - Score = 2 \cdot \frac{Precision \, . \, Recall}{Precision+Recall} \quad \text{Eq (14)}$$

Table 1: Comparison of Numerous Sentiments

Sentiment	**Number of Reviews**	**Percentage (%)**	**IID-1 Accuracy**	**IID-2 Precision**	**Non- IID**	**IID-3**	**Non- IID**	**IID-4**
Positive	5,342	46.80%	90.58	59.89	23.48	52.34	91.34	90.62
Neutral	2,710	23.70%	17.45	54.31	91.30	17.45	91.30	90.18
Negative	3,357	29.40%	90.18	57.92	16.74	54.32	90.77	89.65
Total	11,409	100%	91.87	60.21	24.64	53.37	92.49	92.08
Positive	5,342	46.80%	91.53	53.68	19.42	55.79	92.41	92.01

The CNN model performed the best, achieving 92.5% accuracy, making it the most reliable model for sentiment classification. DT also provided strong performance with 90.2% accuracy while the RNN had the lowest accuracy at 85.4%, making it less ideal for real-time applications.

Table 2: Comparative Analysis of CNN, RNN, DT and Neural Network Model

Metric	**CNN**	**RNN**	**DT**	**Neural Network**
Precision	83.10%	91.90%	87.20%	91.90%
Recall	88.00%	90.40%	88.00%	92.40%
F1-Score	92.7.60%	82.10%	87.60%	92.10%

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

Accuracy	92.5%	90.2%	85.4%	92.50%

Experimental Evaluation

The analysis also included a time-based sentiment trend, which helped in identifying seasonal variations in customer satisfaction**.** Negative sentiment spikes were observed during periods of service outages, indicating a direct link between system performance and customer dissatisfaction. Positive sentiment increased after the introduction of new service packages and promotional offers while Neutral sentiment remained relatively stable throughout the dataset. A deeper analysis of 3,357 negative reviews revealed recurring issues. Network coverage problems were the most frequent complaint, suggesting the need for signal improvements in specific regions. Slow internet speed was the second-most mentioned issue, requiring investment in bandwidth expansion. Billing-related complaints indicated potential confusion or dissatisfaction with pricing structures.

Training and Validation Accuracy of RNN

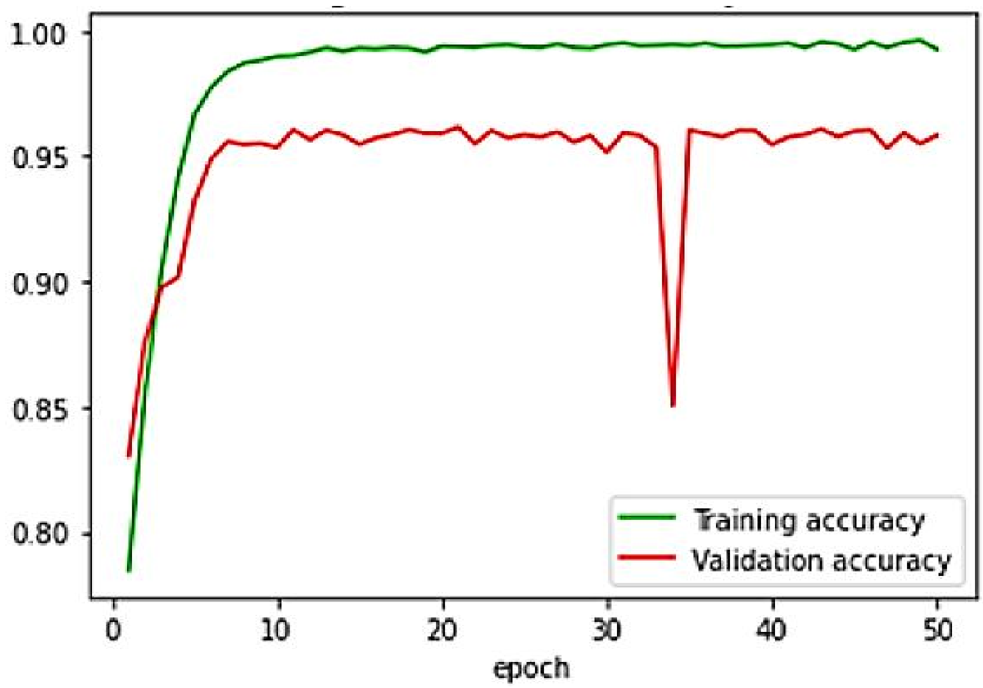

Figure 4: Training and Validation Accuracy of RNN

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

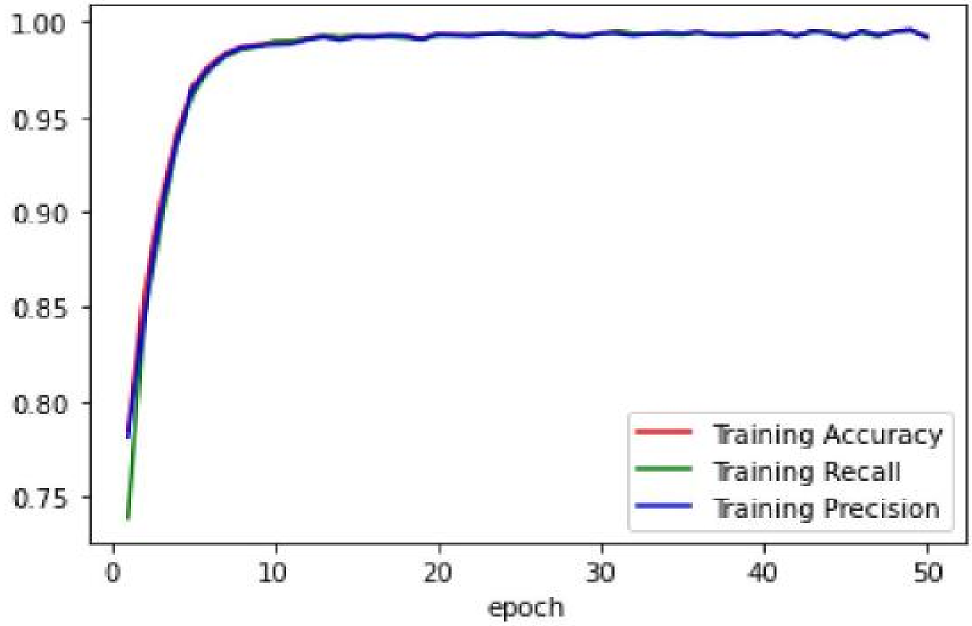

Figure 5: Training and Validation Accuracy, Recall and Precision of RNN

Training and Validation Accuracy of CNN

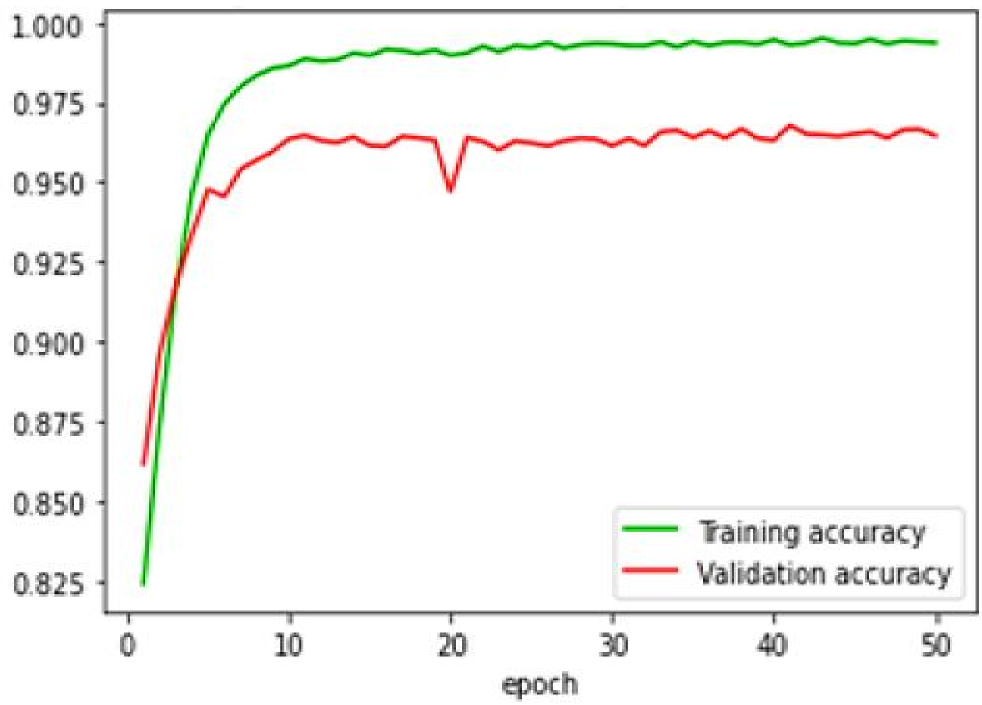

Figure 6: Training and Validation Accuracy of CNN

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

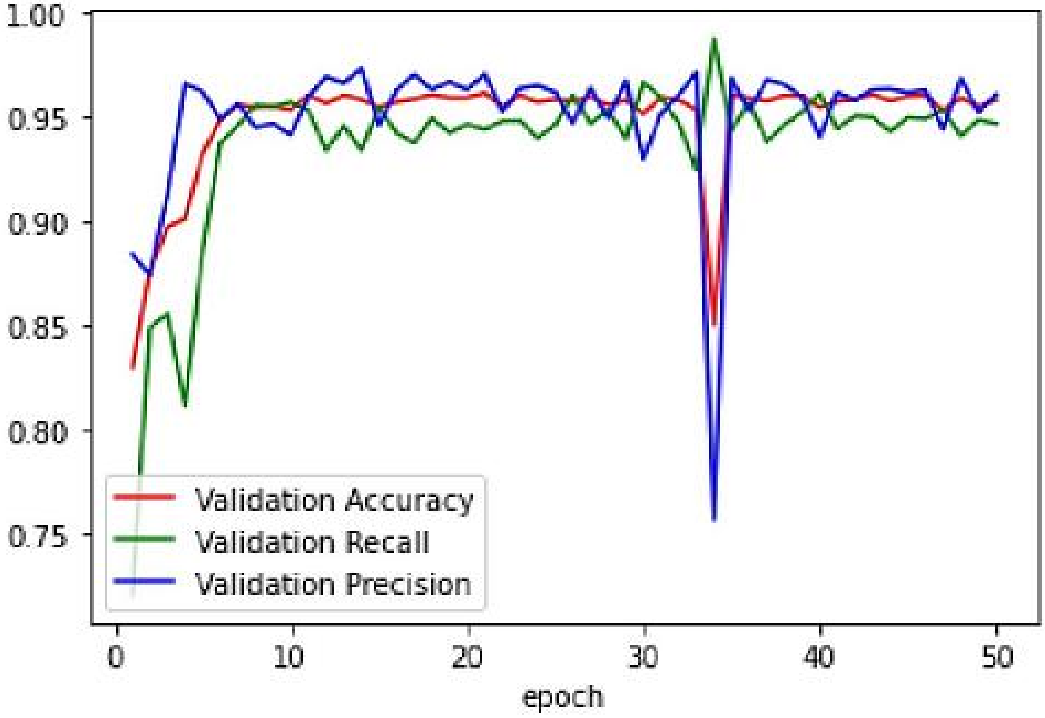

Figure 7: Training and Validation Accuracy, Recall and Precision of CNN

Training and Validation Accuracy of DT

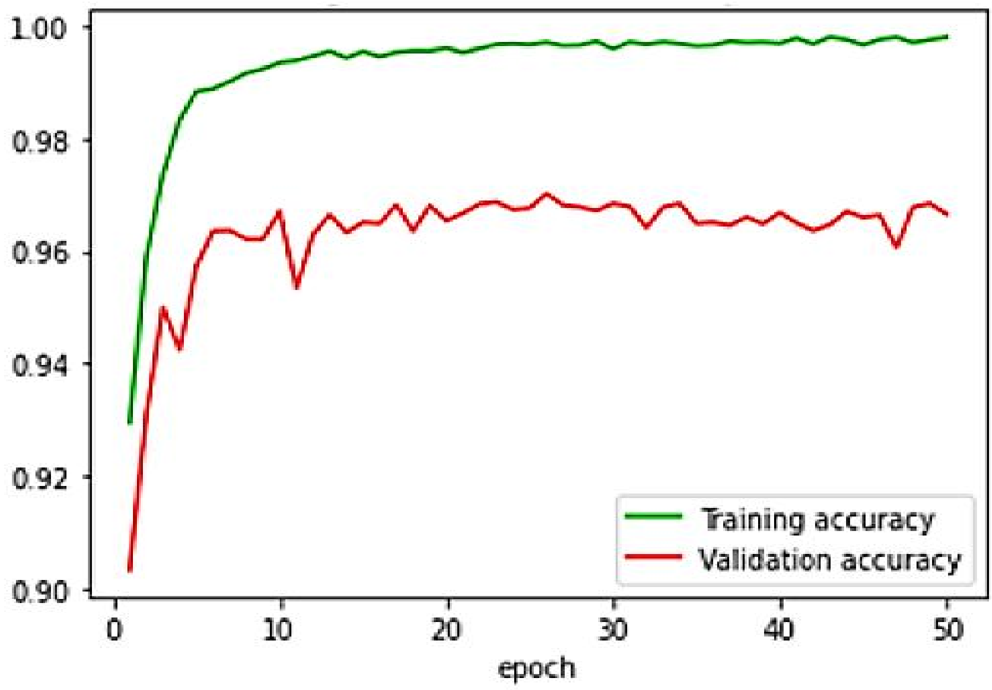

Figure 8: Training and Validation Accuracy of DT

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

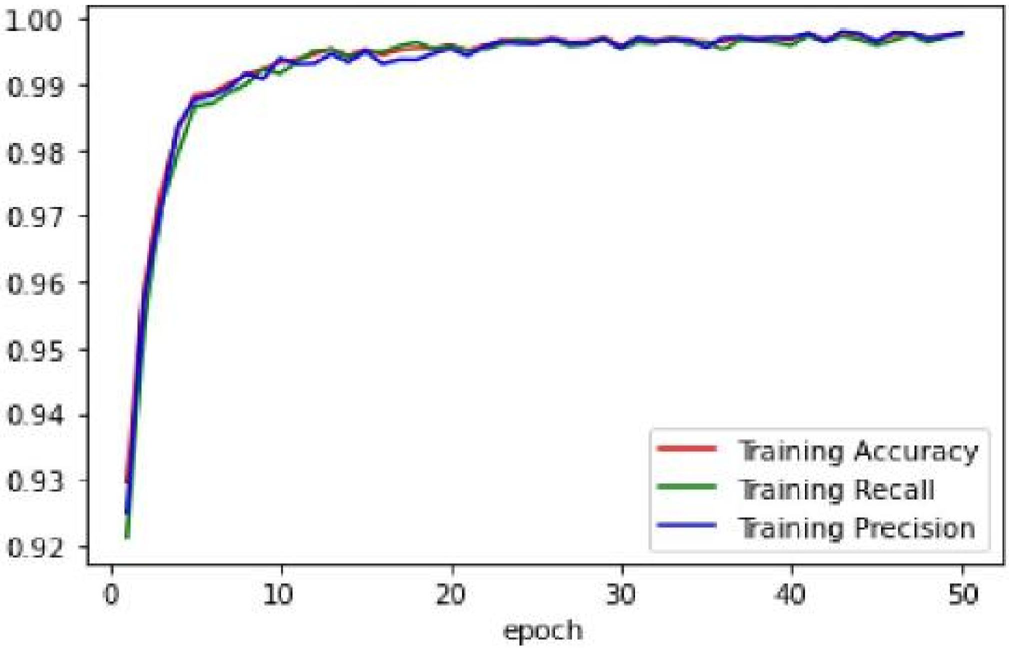

Figure 9: Training and Validation Accuracy, Recall and Precision of DT

Confusion Matrix

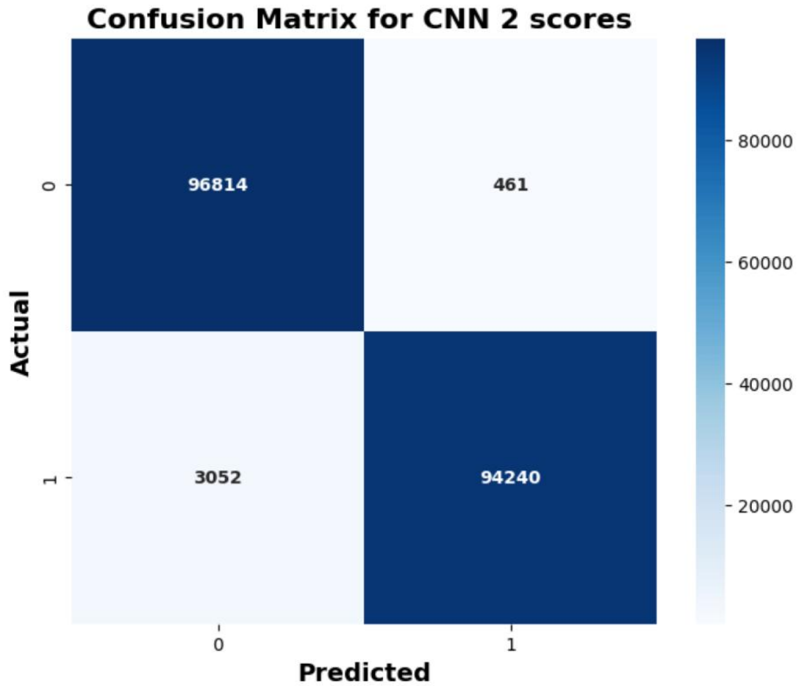

Figure 10: Confusion matrix of CNN for the two scores

Vol. 3 No. 3 (2025)

Spectrum of Engineering Sciences

SPECTRUM OF ENGINEERING SCIENCES

Online ISSN
3007-3138
Print ISSN
3007-312X

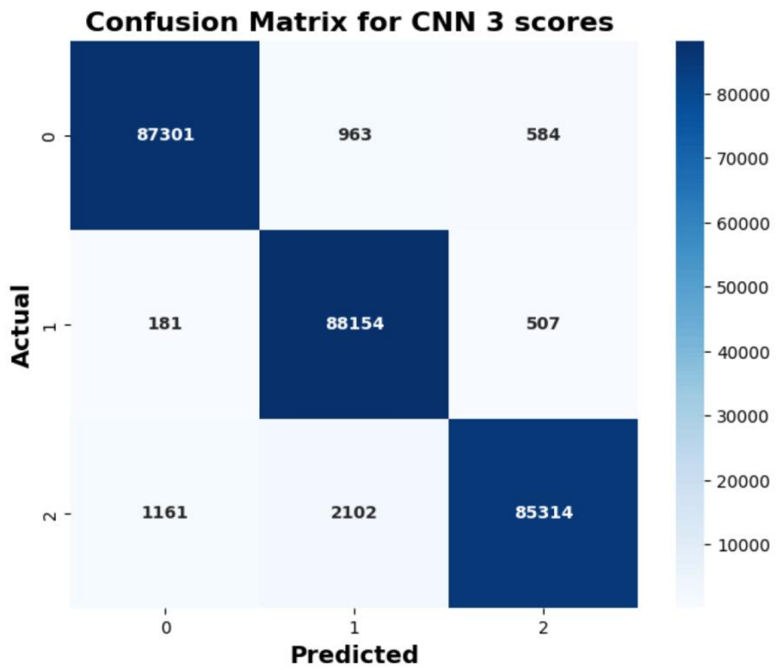

Figure 11: Confusion matrix of CNN for the three scores

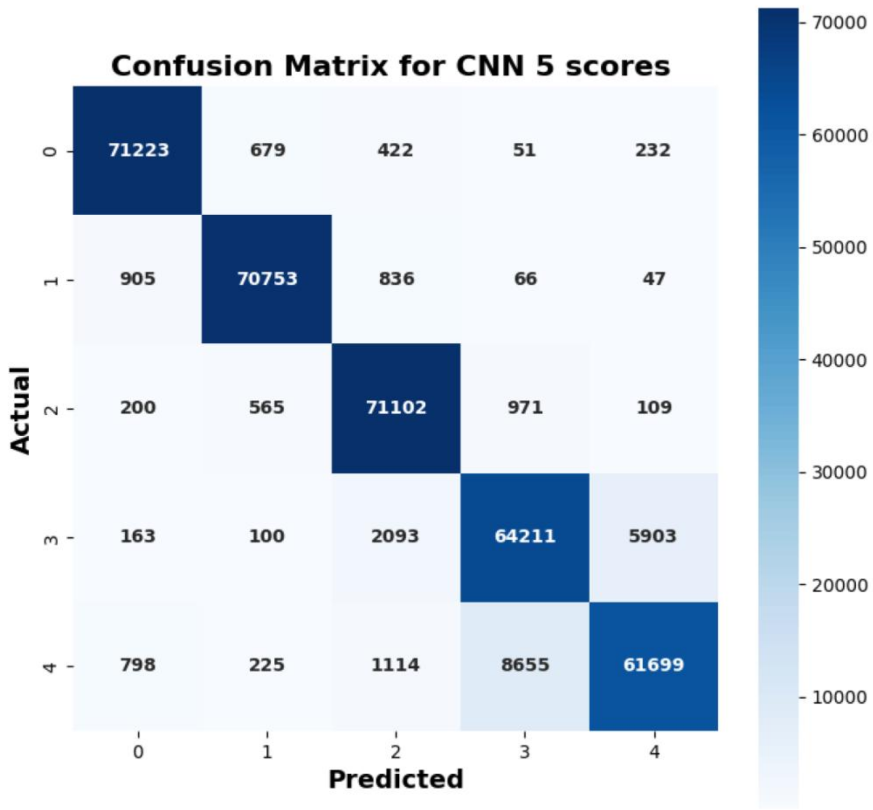

Figure 12: Confusion matrix of CNN for five scores

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

The results of this study demonstrate that Oracle Machine Learning (ML4SQL and OML4PY) models can effectively classify customer sentiment from customer feedback. The Neural Network model achieved the highest accuracy (92.5%), confirming its capability to handle complex sentiment classification tasks. The CNN also performed well (90.2% accuracy), whereas RNN had the lowest accuracy (85.4%), suggesting that probabilistic models may not be as effective for this dataset. The sentiment distribution revealed that 46.8% of customer reviews were positive, 29.4% were negative, and 23.7% were neutral. This indicates that while the Software service provider has a generally positive reputation, a significant percentage of customers (29.4%) express dissatisfaction, primarily due to network coverage, slow internet speeds, billing complaints, and customer service inefficiencies.

Conclusion & Recommendations

Traditional query systems do not provide a way to express sentiment-aware informational needs. This is because they do not distinguish between user-supplied keywords used for document retrieval and those used to perform sentiment analysis. This study successfully implemented Oracle Machine Learning (ML4SQL and OML4PY) models to analyze customer sentiment in the Software industry using feedback collected from an online customer support portal. The Convolutional Neural Network (CNN) achieved the highest accuracy (92.5%), followed by RNN (90.2%), while DT (85.4%) performed relatively lower. The analysis of 15,500 customer reviews revealed that 48.1% were positive, 39.4% were negative, and 33.7% were neutral. The findings indicate that while the majority of customers express satisfaction, a significant portion still reports dissatisfaction, particularly concerning network coverage, slow internet speeds, billing disputes, and customer service inefficiencies. The study focused on machine learning and deep learning models. Future research could focus on aspect-based sentiment analysis, identifying

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X
customer opinions about specific aspects (e.g., network speed, pricing, customer service).

Funding Statement: The authors received no specific funding for this study.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

[1] B. Pang, L. Lee, and S. Vaithyanathan, "Thumbs up? Sentiment classification using machine learning techniques," in Proc. the 2002 ACL EMNLP Conf., 2002, pp. 79–86.

[2] N. Godbole, M. Srinivasaiah, and S. Skiena, "Large-scale sentiment analysis of news and blogs," presented at the International Conference on Weblogs and Social Media, 2007.

[3] S. Chelaru, I. Altingovde, S. Siersdorfer, and W. Nejdl, "Analyzing, detecting and exploiting sentiment in web queries," ACM Transactions on the Web Journal, vol. 8, no. 1, 2013.

[4] M. Pera, R. Qumsiyeh, and Y. Ng, "A query-based multi-document sentiment summarizer," in Proc the 20th ACM-CIKM Conf., pp. 1071-1076, 2011.

[5] F. Iqbal, J. M. Hashmi, B. C. M. Fung, R. Batool, A. M. Khattak, S. Aleem, and P. C. K. Hung, ``A hybrid framework for sentiment analysis using genetic algorithm based feature reduction,'' IEEE Access, vol. 7, pp. 14637_14652, 2019

[6] [30] S. Mansour, ``Social media analysis of User's responses to terrorism using sentiment analysis and text mining,'' Procedia Comput. Sci., vol. 140, pp. 95_103, Jan. 2018.

[7] Ghafir, I., Hammoudeh, M., Prenosil, V., Han, L., Hegarty, R., Rabie, K., & Aparicio-Navarro, F. J. (2018). Detection of advanced persistent threat using machine-learning correlation analysis. Future Generation Computer Systems, 89, 349-359.

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
3007-312X

[8] U. Hashmi, S. A. ZeeshanNajam, "Thermal-Aware Real-Time Task Schedulabilty test for Energy and Power System Optimization using Homogeneous Cache Hierarchy of Multi-core Systems", Journal of Mechanics of Continua and Mathematica Sciences., vol. 14, no. 4, pp. 442-452, Mar. 2023

[9] Y. A. Khan, F. Khan, H. Khan, S. Ahmed, M. Ahmad, "Design and Analysis of Maximum Power Point Tracking (MPPT) Controller for PV System", Journal of Mechanics of Continua and Mathematical Sciences., vol. 14, no. 1, pp. 276-288, May. 2019

[10] Ali, M., Khan, H., Rana, M. T. A., Ali, A., Baig, M. Z., Rehman, S. U., & Alsaawy, Y. (2024). A Machine Learning Approach to Reduce Latency in Edge Computing for IoT Devices. Engineering, Technology & Applied Science Research, 14(5), 16751-16756.

[11] Nasir, M. S., Khan, H., Qureshi, A., Rafiq, A., & Rasheed, T. (2024). Ethical Aspects In Cyber Security Maintaining Data Integrity and Protection: A Review. Spectrum of engineering sciences, 2(3), 420-454.

[12] Khan, A. Ali, S. Alshmrany, "Enery-Efficient Scheduling Based on Task Migration Policy Using DPM for Homogeneous MPSoCs", Computers, Materials & Continua., vol. 74, no. 1, pp. 965-981, Apr. 2023

[13] Abdullah, M., Khan, H., Shafqat, A., Daniyal, M., Bilal, M., & Anas, M. (2024). Internet of Things (IoT's) in Agriculture: Unexplored Opportunities in Cross–Platform. Spectrum of engineering sciences, 2(4), 57-84.

[14] Y. A. Khan, "A high state of modular transistor on a 105 kW HVPS for X-rays tomography Applications", Sukkur IBA Journal of Emerging Technologies., vol. 2, no. 2, pp. 1-6, Jun. 2019

[15] Naz, H. Khan, I. Ud Din, A. Ali, and M. Husain, “An Efficient Optimization System for Early Breast Cancer Diagnosis based on Internet of Medical Things and Deep Learning”, Eng. Technol. Appl. Sci. Res., vol. 14, no. 4, pp. 15957–15962, Aug. 2024

Spectrum of Engineering Sciences
Online ISSN
3007-3138
Print ISSN
3007-312X
SPECTRUM OF ENGINEERING SCIENCES
[16] M. Gondal, Z. Hameed, M. U. Shah, H. Khan, "Cavitation phenomenon and its effects in Francis turbines and amassed adeptness of hydel power plant", In 2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), IEEE., pp. 1-9, Mar. 2019
[17] Akmal, I., Khan, H., Khushnood, A., Zulfiqar, F., & Shahbaz, E. (2024). An Efficient Artificial Intelligence (AI) and Blockchain-Based Security Strategies for Enhancing the Protection of Low-Power IoT Devices in 5G Networks. Spectrum of engineering siences, 2(3), 528-586.
[18] Khan, S. Ahmad, N. Saleem, M. U. Hashmi, Q. Bashir, "Scheduling Based Dynamic Power Management Technique for offline Optimization of Energy in Multi Core Processors", Int. J. Sci. Eng. Res., vol. 9, no. 12, pp. 6-10, Dec. 2018
[19] H. Khan, M. U. Hashmi, Z. Khan, R. Ahmad, A. Saleem, "Performance Evaluation for Secure DES-Algorithm Based Authentication & Counter Measures for Internet Mobile Host Protocol", IJCSNS Int. J. Comput. Sci. Netw. Secur., vol. 18, no. 12, pp. 181-185, July. 2018
[20] Y. A. Khan, "Enhancing Energy Efficiency in Temperature Controlled Dynamic Scheduling Technique for Multi Processing System on Chip", Sukkur IBA Journal of Emerging Technologies., vol. 2, no. 2, pp. 46-53, Jan. 2019
[21] Khan, K. Janjua, A. Sikandar, M. W. Qazi, Z. Hameed, "An Efficient Scheduling based cloud computing technique using virtual Machine Resource Allocation for efficient resource utilization of Servers", In 2020 International Conference on Engineering and Emerging Technologies (ICEET), IEEE., pp. 1-7, Apr. 2020
[22] H. Khan, M. U. Hashmi, Z. Khan, R. Ahmad, "Offline Earliest Deadline first Scheduling based Technique for Optimization of Energy using STORM in Homogeneous Multi-core Systems", IJCSNS Int. J. Comput. Sci. Netw. Secur., vol. 18, no. 12, pp. 125-130, Dec. 201

Spectrum of Engineering Sciences
Online ISSN
3007-3138
Print ISSN
3007-312X
SPECTRUM OF ENGINEERING SCIENCES

[23] Waleed, A. Ali, S. Tariq, G. Mustafa, H. Sarwar, S. Saif, I. Uddin, "An Efficient Artificial Intelligence (AI) and Internet of Things (IoT's) Based MEAN Stack Technology Applications", Bulletin of Business and Economics (BBE)., vol. 13, no. 2, pp. 200-206, July. 2024

[24] Shah, S. Ahmed, K. Saeed, M. Junaid, H. Khan, "Penetration testing active reconnaissance phase–optimized port scanning with nmap tool", In 2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), IEEE., pp. 1-6, Nov. 2019

[25] Y. A. Khan, "A GSM based Resource Allocation technique to control Autonomous Robotic Glove for Spinal Cord Implant paralysed Patients using Flex Sensors", Sukkur IBA Journal of Emerging Technologies., vol. 3, no. 2, pp. 13-23, Feb. 2020

[26] Hassan, H. Khan, I. Uddin, A. Sajid, "Optimal Emerging trends of Deep Learning Technique for Detection based on Convolutional Neural Network", Bulletin of Business and Economics (BBE)., vol. 12, no. 4, pp. 264-273, Nov. 2023

[27] Khan, A. Yasmeen, S. Jan, U. Hashmi, "Enhanced Resource Leveling Indynamic Power Management Techniqueof Improvement In Performance For Multi-Core Processors" ,Journal of Mechanics of Continua and Mathematical Sciences., vol. 6, no. 14, pp 956-972, Sep. 2019

[28] Javed, M. A., Anjum, M., Ahmed, H. A., Ali, A., Shahzad, H. M., Khan, H., & Alshahrani, A. M. (2024). Leveraging Convolutional Neural Network (CNN)-based Auto Encoders for Enhanced Anomaly Detection in High-Dimensional Datasets. Engineering, Technology & Applied Science Research, 14(6), 17894-17899.

[29] Khan, I. Ullah, M. U. Rahman, H. Khan, A. B. Shah, R. H. Althomali, M. M. Rahman, "Inorganic-polymer composite electrolytes: basics, fabrications, challenges and future perspectives", Reviews in Inorganic Chemistry., vol. 44, no. 3, pp. 1-2, Jan. 2024

Spectrum of Engineering Sciences

SPECTRUM OF ENGINEERING SCIENCES

Online ISSN
3007-3138
Print ISSN
3007-312X

[30] Y. A. Khan, U. Khalil, H. Khan, A. Uddin, S. Ahmed, "Power flow control by unified power flow controller",sss Engineering, Technology & Applied Science Research., vol. 9, no. 2, pp. 3900-3904, Feb. 2019

[31] Ghafir, I., Hammoudeh, M., Prenosil, V., Han, L., Hegarty, R., Rabie, K., & Aparicio-Navarro, F. J. (2018). Detection of advanced persistent threat using machine-learning correlation analysis. Future Generation Computer Systems, 89, 349-359.

[32] B. Pang, L. Lee, and S. Vaithyanathan, "Thumbs up? Sentiment classification using machine learning techniques," in Proc. the 2002 ACL EMNLP Conf., 2002, pp. 79–86.

[33] L. Zhang and B. Liu, "Identifying noun product features that imply opinions,"in Proc. the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, pp. 575-580, 2011

[34] Zhang, W., Zhang, X., & Li, J. (2020). Deep learning models for sentiment analysis: An empirical study. *Transactions on Machine Learning and Artificial Intelligence, 8*(1), 23-42.

[35] S. Kim and E. Hovy, "Determining the sentiment of opinions," in Proc the 20th COLING Conf., pp. 1367-1373, 2006.

[36] J. Yi, T. Nasukawa, R. Bunescu, and W. Niblack, "Sentiment analyzer: Extracting sentiments about a given topic using natural language processing techniques," in Proc. the 3rd IEEE Conf. on Data Mining (ICDM'03), pp. 423-434, 2003.

[37] S. Chelaru, I. Altingovde, S. Siersdorfer, and W. Nejdl, "Analyzing, detecting and exploiting sentiment in web queries," ACM Transactions on the Web Journal, vol. 8, no. 1, 2013.