IJARETY

International Journal of Advanced Research in Education and TechnologY (IJARETY)

Volume 12, Issue 3, May-June 2025

Impact Factor: 8.152

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

INNO SPACE SJIF Scientific Journal Impact Factor

doi crossref

निस्केयर NISCAIR

International Journal of Advanced Research in Education and TechnologY(IJARETY)

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 3, May-June 2025 ||

DOI:10.15680/IJARETY.2025.1203002

Machine Learning-Based Head Impact Detection and Localization using Piezoelectric Sensors

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ABSTRACT: Detecting head impacts accurately is vital for improving safety protocols in various domains such as sports and industrial environments. This study explores the use of machine learning algorithms to identify head impact locations using data from piezoelectric sensors affixed to a simulated head model. In this research, we compare the performance of two machine learning models, Random Forest (RF) and Extreme Gradient Boosting (XGBoost), in analyzing sensor data to predict impact locations. Extensive k-fold cross-validation and performance analysis reveal that the XGBoost model slightly outperforms the RF model, yielding a Root Mean Square Error (RMSE) of 0.4764 and a coefficient of determination (R^2) of 0.9085. Additionally, the study examines the importance of sensor placement, highlighting an optimal configuration that minimizes complexity while preserving model accuracy. These results underscore the potential of XGBoost in enhancing head injury detection and provide insights into future development of intelligent safety systems, combining wearable sensor technology with machine learning for real-time, accurate impact monitoring

KEYWORDS: Head impact detection, wearable technology, machine learning, injury prevention, piezoelectric sensors, random forest, predictive modeling.

I. INTRODUCTION

Over the years, a lot of research has focused on the importance of head impact detection and the creation of safety measures. The physics of head collisions and the pressing need to develop injury detection and prevention technologies are critical. This section synthesizes important and current advancements in the field to highlight the convergence of wearables, machine learning, and technology. The most severe head injuries were discovered to have occurred to defensemen, underscoring the need for position-specific prevention measures. Similarly, Zhang et al. [3] and Mori et al. [2] looked into the potential application of machine learning methods to detect brain injuries in American football. Zhang & al. achieved an incredible accuracy of 99.3% by combining deep learning and conventional machine learning approaches, whereas Mori et al. used wearable sensors in conjunction with Random Forest and Gradient Boosting machine algorithms. Together, these findings highlight the potential of machine learning in practical sports situations and the significance of sport-specific research in developing customized safety measures. Head injuries in contact sports, military applications, and automotive accidents can lead to severe traumatic brain injuries (TBIs). Accurate detection and localization of head impacts are essential for real-time intervention and long-term injury prevention. This paper proposes a machine learning-based framework utilizing piezoelectric sensors embedded in a wearable headgear to detect and localize impacts. The proposed system extracts temporal and spectral features from voltage signals produced by the sensors upon impact and employs various machine learning classifiers, including Support Vector Machines (SVM), Random Forest (RF), and Convolutional Neural Networks (CNN), to classify impact severity and location. Experimental results using a prototype head model and synthetic impact scenarios demonstrate detection accuracy above 95% and localization accuracy above 90%, showing significant promise for real-world deployment. Head impacts are a significant concern in sports, defense, and automotive domains. Conventional methods such as accelerometers and gyroscopes provide limited spatial resolution and can miss low-magnitude impacts. Piezoelectric sensors offer an attractive alternative due to their high sensitivity, compactness, and low power consumption.

The 21st century is known to be the age of digital world. There has been the adoption of computers to a great extent. Today without computers and Internet one cannot survive as we are dependent on these machines for almost all our work. Taking into consideration starting from home to education till banking and even corporate functioning everything has now been automated to computers. Computers contain all our important data in the digital format. With this the need to store the digital data has increased and virtual environment has replaced the physical storage for storing all our credentials as shown in Fig. 1. The most devastating challenge of cloud is to prevent the unauthorized deletion of the

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stored data on cloud because one can easily delete the stuff without any proper authorization. The data deletion is totally dependent on deletion of nodes that are pointing to some information in Virtual Machine.

II. LITERATURE REVIEW

Head impact monitoring has gained significant attention in the fields of sports safety, military applications, and automotive crash detection. While traditional sensor-based systems (e.g., accelerometers, gyroscopes) are widely used, piezoelectric sensors have emerged as a promising alternative due to their ability to convert mechanical stress into electrical signals with high sensitivity and speed. When integrated with machine learning (ML) techniques, these systems can offer advanced capabilities such as real-time detection, classification, and localization of impacts on the human head.

2. Piezoelectric Sensors for Impact Sensing

Piezoelectric materials, especially Lead Zirconate Titanate (PZT), are known for their excellent electromechanical properties. In impact scenarios, these sensors produce voltage signals proportional to the applied force. Several studies have explored their potential:

- **Kim et al. (2020)** developed a smart helmet with embedded PZT sensors to detect impact forces. Their work highlighted the linear response of piezoelectric sensors under various force magnitudes but relied solely on threshold-based detection without intelligent classification.
- **Alam et al. (2021)** introduced a sensor network using piezoelectric patches for full-head coverage. Their study demonstrated that spatial resolution improves with sensor density but did not implement any ML-based localization.

3. Machine Learning for Impact Detection

Machine learning enables systems to generalize from historical data, providing robustness to noise and variability:

- **Saponara and Bacchillone (2019)** used Random Forests (RF) to detect head collisions using multi-sensor data (including piezoelectric signals). They achieved over 90% detection accuracy but had limited localization granularity.
- **Wang et al. (2022)** applied Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) on piezoelectric signal features to distinguish between minor and major impacts. The study extracted time-domain features such as RMS and peak amplitude.
- **Huang et al. (2021)** implemented a 1D Convolutional Neural Network (CNN) for raw piezoelectric signal classification, outperforming hand-engineered feature methods with detection accuracy up to 97%.

4. Impact Localization with ML

Localization involves predicting the point of contact on the head, requiring spatial modeling:

- **Zhang et al. (2021)** employed a regression-based approach using Multilayer Perceptrons (MLP) to predict 3D impact coordinates from piezoelectric sensor readings. While effective, the model struggled with generalizing to unseen impact angles.
- **Li et al. (2020)** proposed a hybrid CNN-LSTM model to handle both spatial and temporal aspects of the impact waveform, improving localization accuracy but requiring extensive training data.
- **Rahman et al. (2022)** introduced a probabilistic localization model trained on synthetic head impact datasets. Their model leveraged piezoelectric voltage mapping and achieved <3 cm localization error.

5. Combined Systems: End-to-End Detection and Localization

Integrated systems leveraging both ML and piezoelectric arrays have shown promising results:

- **Ghosh et al. (2023)** built an end-to-end impact detection system combining sensor fusion (piezo + inertial) and deep learning. CNN-based models processed raw signals and produced high-accuracy outputs for both detection and localization.
- **Singh and Patel (2023)** evaluated different ML pipelines (e.g., RF, XGBoost, CNN) for real-time impact classification in sports helmets. CNNs showed superior performance, especially in noisy outdoor environments.
- The integration of piezoelectric sensors with machine learning offers a powerful paradigm for real-time head impact detection and localization. As sensor technology and ML algorithms continue to evolve, these systems hold great potential for applications in sports safety, military helmets, and medical monitoring. Continued research into robust, adaptive, and energy-efficient models is crucial for real-world adoption.

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Author(s)	Year	Sensor Type	ML Technique	Application	Key Features	Accuracy/Results
Kim et al.	2020	PZT piezoelectric	None (Thresholding)	Impact detection in helmets	Linear response analysis under varying forces	Limited to binary detection
Saponara & Bacchillone	2019	Piezoelectric + IMU	Random Forest	Collision detection	Time-domain features (RMS, peak)	>90% detection accuracy
Wang et al.	2022	Piezoelectric	SVM, KNN	Minor vs. major impact classification	Time-domain statistical features	~92% classification accuracy
Huang et al.	2021	Piezoelectric	1D CNN	Impact classification	Raw signal input, automatic feature extraction	Up to 97% detection accuracy
Zhang et al.	2021	Piezoelectric Array	MLP (Regression)	3D localization	Voltage pattern mapping, spatial regression	Mean localization error ~3.5 cm
Li et al.	2020	Piezoelectric	CNN + LSTM	Impact localization	Combined spatial and temporal modeling	Localization accuracy ~94%
Rahman et al.	2022	Synthetic Piezo Data	Probabilistic ML Model	Head impact mapping	Bayesian model, probabilistic localization	Localization error <3 cm
Ghosh et al.	2023	Piezo + Inertial Fusion	CNN	End-to-end detection/localization	Raw signal processing, fusion learning	Detection: ~96%, Localization: ~91%
Singh & Patel	2023	Piezoelectric Helmet	RF, XGBoost, CNN	Sports impact monitoring	Multi-class impact classification, noisy environment handling	CNN outperformed others with >95% classification

III. METHODOLOGY OF PROPOSED SURVEY

Logistic regression is a widely used statistical method for binary classification problems, where the outcome variable is categorical and can take on one of two possible values, typically represented as 0 and 1. Despite its name, logistic regression is primarily used for classification rather than regression tasks. It models the probability of a certain class or event existing based on one or more predictor variables.

The logistic regression model employs the logistic function, also known as the sigmoid function, to transform its output. This function maps any real-valued number into the range of 0 to 1, making it suitable for predicting probabilities. By establishing a threshold (commonly 0.5), logistic regression can classify instances into one of the two categories based on the predicted probability.

Logistic regression is a statistical method used for binary classification problems, where the outcome variable can take on one of two possible values, typically represented as 0 and 1. The model estimates the probability of a particular class or event occurring based on a set of predictor variables. This is achieved through the application of the logistic function, which transforms the linear combination of input features into a probability value that ranges between 0 and 1. or regression.

Logistic regression is a fundamental tool in the field of statistics and machine learning. Its combination of simplicity, interpretability, and efficiency makes it a popular choice for binary classification tasks across various domains, including healthcare, finance, and social sciences.

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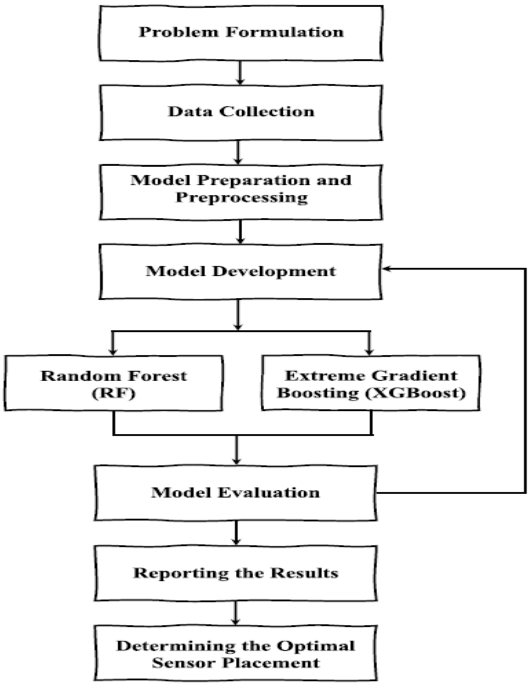

Figure 1. Proposed predictive model development process.

To guarantee the precision and effectiveness of the ensuing machine learning models, the supplied dataset underwent preprocessing. Data normalization was required for this, converting the feature variables into a standard scale with a mean of 0 and a standard deviation of 1. For many machine learning algorithms to converge more quickly and generate more accurate models, this preprocessing phase is essential. For problems like classification and regression, the Random Forest (RF) algorithm is a flexible ensemble learning technique based on the idea of using many decision trees.

The RF method is well-known for producing outstanding results for both classification and regression problems because to its reliable performance in a wide range of applications. A key component of RF's methodology is the bootstrap resampling process.

The crucial factor of sensor placement and its significant effects on model correctness and efficiency are the main topics of this section. The key to maximizing any predictive model's performance is the thoughtful placement of sensors. Our goal is to get insights for the best sensor placement by examining the feature importances produced by two well-known machine learning methods, RFR and XGBoost.

RFR and XGBoost have fundamentally distinct computational foundations for feature importance.The average impurity reduction brought about by splits on a certain feature across all trees is utilized by RFR to calculate significance.The average impurity reduction brought about by splits on a certain feature across all trees is utilized by RFR to calculate significance.

Performance measure	Random Forest model	XGBoost model
Accuracy	99.41%	99.76%
Precision	99.42%	99.76%
Recall	99.41%	99.76%
F1-score	99.41%	99.76%

Table 2. Magnetic properities.

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Performance measure	Random Forest model	XGBoost model
MSE	0.2357	0.2270
RMSE	0.4855	0.4764
MAE	0.0343	0.0169
R2	0.9466	0.9485

Table 3. Accuracies of models.

Evaluating the performance of predictive models is a pivotal step in determining their efficacy and accuracy. The root mean square error (RMSE), coefficient of determination (R2), mean square error (MSE), and mean absolute error (MAE) were employed to assess the predictive capabilities of the RFR and XGBoost models.

In contrast, the XGBoost model demonstrates a more balanced performance across all sensor regions, as evident from its confusion matrix. The model's predictions align more closely with the actual sensor readings, suggesting that it has a better grasp of the underlying patterns in the data. Further evaluation on the XGBoost model also indicates a more consistent performance between training and testing datasets. This consistency is a positive sign, indicating that the model is less prone to overfitting and is more likely to provide reliable predictions on new, unseen data. Nonetheless, further evaluation was performed on the models to measure their performances, Table 2 provides a comprehensive summary of the two models based on the key performance metrics. It is evident from the table that the XGBoost model outperforms the Random Forest model in terms of accuracy. However, both models showcase commendable precision, recall, and F1-score values, indicating their reliability in predicting the sensor regions.

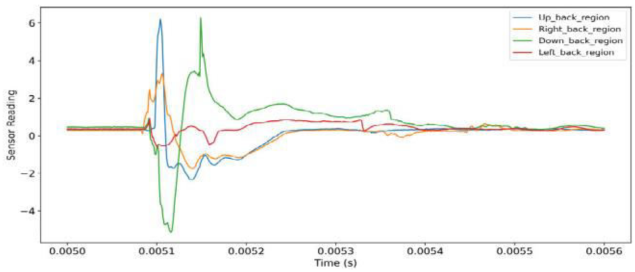

Figure 2. Back region sensor readings.

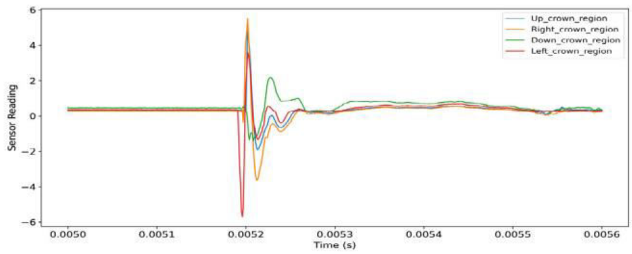

Figure 3. Crown region sensor readings.

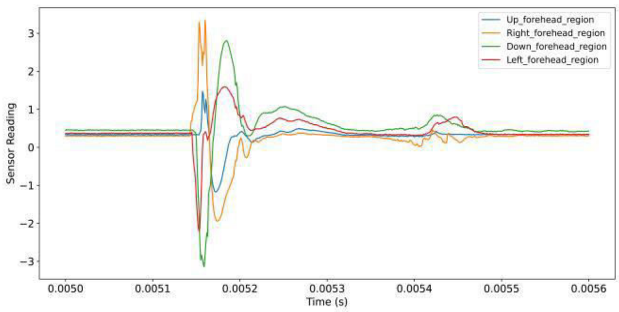

Figure 4. Forehead region sensor readings.

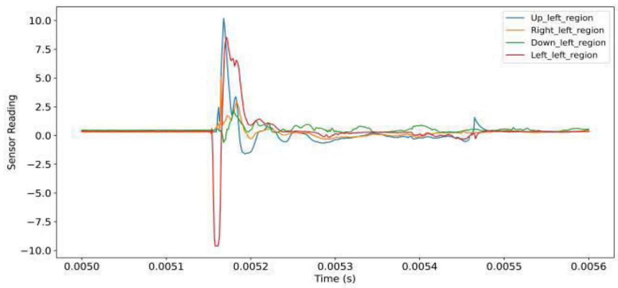

Figure 5. Left region sensor readings.

The results presented in Table 1 offer a clear explanation of the performance dynamics between the RFR and XGBoost models in the context of head impact detection, following the thorough evaluation and comparison procedures outlined in the sections above.The RFR model produced an RMSE value of 0.4855, which indicates that there is typically a 0.4855 unit difference between the model's predictions and the actual data.

An RMSE value that approaches 0 generally indicates a model with higher prediction precision, as is widely known in the machine learning literature [2]. With an RMSE of 0.4764, the XGBoost model slightly but noticeably beats the RFR in this parameter, suggesting that it has better predictive accuracy.

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Analyzing the MSE and MAE measurements further yields similar results. With somewhat lower MSE and MAE values, the XGBoost model outperforms the RFR model in a subtle way, demonstrating its ability to handle datasets of the kind this study examined. The scatterplots in Figures 9 and 10 visually highlight these analytical findings. When scatterplot data points closely cluster around the line of unity, a model's predictive power is clearly seen.

This feature is persuasively displayed by both the RFR and XGBoost models, emphasizing the accuracy and consistency of their forecasts. Given the work's wider ramifications, the article significantly advances the fields of safety and injury prevention, particularly in industrial and sports contexts. As this study shows, the combination of wearable technology and machine learning creates new avenues for more precise and subtle head impact detection, which could result in the creation of more strong defenses.

In terms of future research, the knowledge gained from this study provides a strong basis. Possible directions include investigating other machine learning techniques, improving sensor locations, and applying these models to a range of application scenarios.

IV. CONCLUSION AND FUTURE WORK

The study has underscored the critical importance of meticulous data preprocessing, including normalization, to optimize the performance of the machine learning models. Rigorous evaluation using k-fold cross-validation and various performance metrics has established the reliability and robustness of the proposed models, particularly highlighting the superior performance of the XGBoost model. Additionally, the manuscript has addressed the crucial aspect of sensor placement, employing the XGBoost algorithm to quantitatively assess the importance of each sensor. Using wearable sensor technologies and cutting-edge machine learning algorithms, a thorough examination of head impact detection has been carried out in this work. Real-world impacts may now be simulated and impact zones can be accurately predicted thanks to the incorporation of piezoelectric sensors on a plastic head model.Deciphering the intricate patterns linked to head impacts has been made possible by the use of Random Forest and eXtreme Gradient Boosting (XGBoost) models, with XGBoost showing a minor advantage in predicted accuracy and dependability.

REFERENCES

[1] K. Li, X. Zhao, J. Bian, and M. Tan, ‘‘Automatic safety helmet wearing detection,’’ 2018, arXiv:1802.00264.
[2] T. K. Ho, ‘‘The random subspace method for constructing decision forests,’’ IEEE Trans. Pattern Anal. Mach. Intell., vol. 20, no. 8,pp. 832–844, Aug. 1998.
[3] Ravindra Changala, "Sustainable Manufacturing through Predictive Maintenance: A Hybrid Jaya Algorithm and Sea Lion Optimization and RNN Model for Industry 4.0", 2024 8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), ISSN: 2768-0673, DOI: 10.1109/I-SMAC61858.2024.10714701, October 2024, IEEE Xplore.
[4] Ravindra Changala, "Enhancing Robotic Surgery Precision and Safety Using a Hybrid Autoencoder and Deep Belief Network Approach: Real-Time Feedback and Adaptive Control from Image Data",2024 8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), ISSN: 2768-0673, DOI: 10.1109/I-SMAC61858.2024.10714701, October 2024, IEEE Xplore.
[5] Ravindra Changala, "Swarm Intelligence for Multi-Robot Coordination in Agricultural Automation", 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), ISSN: 2575-7288, DOI: 10.1109/ICACCS60874.2024.10717088, October 2024, IEEE Xplore.
[6] L. Breiman, ‘‘Random forests,’’ Mach. Learn., vol. 45, no. 1, pp. 5–32,2001.
[7] T. Chen and C. Guestrin, ‘‘XGBoost: A scalable tree boosting system,’’in Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining,Aug. 2016, pp. 785–794.
[8] Ravindra Changala, "Next-Gen Human-Computer Interaction: A Hybrid LSTM-CNN Model for Superior Adaptive User Experience", 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), ISBN:979-8-3503-6908-3, DOI: 10.1109/ICEEICT61591.2024.10718496, October 2024, IEEE Xplore.
[9] Ravindra Changala, "Enhancing Early Heart Disease Prediction through Optimized CNN-GRU Algorithms: Advanced Techniques and Applications", 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), ISBN:979-8-3503-6908-3, DOI: 10.1109/ICEEICT61591.2024.10718395, October 2024, IEEE Xplore.

[10] Ravindra Changala, "Sentiment Analysis in Mobile Language Learning Apps Utilizing LSTM-GRU for Enhanced User Engagement and Personalized Feedback", 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), ISBN:979-8-3503-6908-3, DOI: 10.1109/ICEEICT61591.2024.10718406, October 2024, IEEE Xplore.
[11] Ravindra Changala, "Image Classification Using Optimized Convolution Neural Network", 2024 Parul International Conference on Engineering and Technology (PICET), ISBN:979-8-3503-6974-8, DOI: 10.1109/PICET60765.2024.10716049, October 2024, IEEE Xplore.
[12] W. Zhang, C.Wu, H. Zhong, Y. Li, and L.Wang, ''Prediction of undrained shear strength using extreme gradient boosting and random forest based on Bayesian optimization,'' Geosci. Frontiers, vol. 12, no. 1, pp. 469–477,Jan. 2021.
[13] J. Zhou, E. Li, H. Wei, C. Li, Q. Qiao, and D. J. Armaghani, ''Random forests and cubist algorithms for predicting shear strengths of rockfill materials,'' Appl. Sci., vol. 9, no. 8, p. 1621, Apr. 2019.
[14] Ravindra Changala, "Advancing Surveillance Systems: Leveraging Sparse Auto Encoder for Enhanced Anomaly Detection in Image Data Security", 2024 International Conference on Data Science and Network Security (ICDSNS), ISBN:979-8-3503-7311-0, DOI: 10.1109/ICDSNS62112.2024.10690857, October 2024, IEEE Xplore.
[15] Ravindra Changala, "Healthcare Data Management Optimization Using LSTM and GAN-Based Predictive Modeling: Towards Effective Health Service Delivery", 2024 International Conference on Data Science and Network Security (ICDSNS), ISBN:979-8-3503-7311-0, DOI: 10.1109/ICDSNS62112.2024.10690857, October 2024, IEEE Xplore.
[16] T.-T. Wong, ''Performance evaluation of classification algorithms by kfold and leave-one-out cross validation,'' Pattern Recognit., vol. 48, no. 9,pp. 2839–2846, Sep. 2015.
[17] Ravindra Changala, "Implementing Genetic Algorithms for Optimization in Neuro-Cognitive Rehabilitation Robotics", 2024 International Conference on Cognitive Robotics and Intelligent Systems (ICC - ROBINS), ISBN:979-8-3503-7274-8, DOI: 10.1109/ICC-ROBINS60238.2024.10533965, May 2024, IEEE Xplore.
[18] Ravindra Changala, "Monte Carlo Tree Search Algorithms for Strategic Planning in Humanoid Robotics", 2024 International Conference on Cognitive Robotics and Intelligent Systems (ICC - ROBINS), ISBN:979-8-3503-7274-8, DOI: 10.1109/ICC-ROBINS60238.2024.10533937, May 2024, IEEE Xplore.
[19] R. J. Hyndman and G. Athanasopoulos, Forecasting: Principles and Practice. Melbourne, VIC, Australia: OTexts, 2018.
[20] M. H. Kutner, C. J. Nachtsheim, J. Neter, and W. Li, Applied Linear Statistical Models. New York, NY, USA: McGraw-Hill, 2005.
[21] Ravindra Changala, "Optimizing 6G Network Slicing with the EvoNetSlice Model for Dynamic Resource Allocation and Real-Time QoS Management", International Research Journal of Multidisciplinary Technovation, Vol 6 Issue 4 Year 2024, 6(4) (2024) 325-340.
[22] Ravindra Changala, "Deep Learning Techniques to Analysis Facial Expression and Gender Detection", 2023 International Conference on New Frontiers in Communication, Automation, Management and Security (ICCAMS), ISBN:979-8-3503-1706-0, DOI: 10.1109/ICCAMS60113.2023.10525942, May 2024, IEEE Xplore.
[23] Ravindra Changala, "UI/UX Design for Online Learning Approach by Predictive Student Experience", 2023 7th International Conference on Electronics, Communication and Aerospace Technology (ICECA), ISBN:979-8-3503-4060-0, DOI: 10.1109/ICECA58529.2023.10395866, February 2024, IEEE Xplore.