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AI-BASED REMOTE HEALTH MONITORING SYSTEM USING IOT AND MACHINE LEARNING

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Article Info

Abstract

The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) in healthcare has revolutionized patient monitoring and disease management. This research explores the development and optimization of AI-based remote health monitoring systems, leveraging IoT devices and machine learning algorithms. The study focuses on improving diagnostic accuracy, real-time data processing, data security, and system integration for enhanced patient care. By addressing challenges such as data reliability, privacy concerns, and computational constraints, this research proposes a novel approach to continuous health monitoring. Several machine learning models, including Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), are employed to analyze health metrics such as heart rate, blood pressure, and ECG data. The findings indicate that the Random Forest model outperforms other algorithms in terms of accuracy, precision, and recall, demonstrating its potential for real-time health monitoring applications. This work provides valuable insights into the application of AI-driven health systems, offering a foundation for future advancements in personalized, cost-effective healthcare solutions.

Keywords:
AI-Based Health Monitoring, Machine Learning, IoT, Real-Time Health Data, Random Forest, Predictive Analytics, Remote Health Monitoring (Expanded).

1. Introduction

The amalgamation of Artificial intelligence (AI) and Internet of things (IoT) in the healthcare has immensely revolutionized the patient monitoring and disease care. The rapid progress of sensor technologies, wireless communication, and machine learning (ML) algorithms has enabled AI-driven RHM solutions that enable real-time monitoring of physiological data and early detection of diseases[1].

With billions of devices connected it is more crucial than ever to effectively manage these devices for long term chronic care conditions. They gather heart rate, blood pressure and levels of oxygen in the blood and can obtain electrocardiogram (ECG) readings, thus allowing healthcare providers to track patients remotely and minimising hospital visits and increasing access to immediate healthcare interventions [2], [3]. AI-powered analytics have the ability to find irregularities in health data, forecast potential medical issues and inform personalized treatments [5], [6].

This landscape is accentuated by the growing burden of chronic diseases, ageing of populations, and a global need for equitable health systems. Remote health monitoring based on AI has a number of advantages such as early disease detection, remote handling of patients, and affordable healthcare [7]. Nevertheless, issues such as data quality, real-time data streaming, system fusion, privacy protection and legal compliance are obstacles to their wide application [8], [9].

This work is targeted at designing, developing and tuning AI enabled remote health monitoring systems to overcome these challenges, specifically focusing on enhancing the diagnostic accuracy, the real-time processing potentials, data security, and integration with the current health service systems. The article investigates several machine learning techniques such as RF, SVM and KNN in the context of analysing healthcare data captured from IoT based wearable sensors. Findings are expected to contribute to personalized healthcare, improving patient outcomes and minimizing demands on the healthcare system.

2. Literature Review

The amalgamation of AI and IoT towards healthcare has enabled noteworthy development in remote health monitoring providing hopeful solutions for early detection and management of disease. This survey investigates main methodologies, available systems and challenges of the AI-empowered health monitoring systems, by concentrating on ML techniques and IoMT in healthcare[10], [11].

2.1 AI and IoT in Healthcare

AI has recently emerged with promising applications in health as automated disease diagnosis, prediction of patient outcome, and personal treatment suggestions. Health data analysis and patient behavior, vital signs, and clinical outcome pattern recognition using ML models like SVM, Random Forest, CNN are regularly used[12], [13], [14]. Such models are useful when dealing with massive complex data from IoT sensors, providing information's that it is not trivial to extract with classical diagnostic techniques[15].

IoT devices (wearable sensors and smart health monitors) support to monitor health indices continuously (e.g., heart-rate, blood pressure, glucose readings, ECG, etc.). Such information can then be communicated to health caregivers instantaneously for remote monitoring of patients and early intervention of potential health hazards[16], [17]. Incorporate AI and IoT into healthcare systems triggers the transition from reactive management of chronic diseases to proactive care, allowing customized and timely services for patients[18].

2.2 Machine Learning for Health Monitoring

Healthcare is one of the most targeted fields for application of machine learning models, particularly classification and prediction for various diseases. Among the most frequently employed algorithms for health data analysis are Random Forest, Support Vector Machines (SVM) and K-Nearest neighbors (KNN) [19], [20]. The ensemble learning algorithm Random Forest is known to be highly accurate while efficient in large datasets and many features [21]. SVM is one of the popular supervised models and it is highly efficient in binary classification, especially when considering complex-bounded data [22]. KNN is non-parametric and is rather intuitive, but may be not very effective for high-dimensional data [23].

Studies have shown that for the analysis of time-series data and medical images, deep learning models (such as CNN and LSTM networks [Long Short-Term Memory (LSTM)]) perform well. For example, CNNs have been widely employed in medical image analysis, where the performance of such networks largely outperforms traditional methods in tasks, such as tumor diagnosis [24], [25]. LSTM networks, which are suitable for processing sequential data, are employed to track patients' health through times and forecast the health changes and potential health events [26], [27].

2.3 AI-Based Remote Health Monitoring: Challenges

Although AI-centric health monitoring applications are touted as having the potential to offer such insights, a number of challenges exist that currently limit their adoption. Real-time data quality and reliability are very challenging problems, given that wearable sensors and IoT (Internet of Things) devices can produce noise and errors [28]. Incorrect or missing information may undermine the efficacy of AI models and result in false diagnoses or overlooked health conditions [29].

Integration of the AI system into the healthcare infrastructure is another challenge. A barrier to care providers having and using the knowledge produced by AI is the paucity of integration between health monitoring systems and electronic medical records and hospital management systems [30]. And reliability and privacy of patient data remains critical, as it must be safely transmitted and stored according to multiple privacy laws (such as HIPAA and GDPR) [31].

2.4 Ethical and Regulatory Considerations

The ethical challenges of AI in healthcare are transparency, accountability and patient consent. AI models, particularly the deep learning packages, serve as black boxes a lot of the time, leaving healthcare staff members dubious regarding the decisions these systems make. The need for explain ability and interpretability of AI models in healthcare is imperative to win the trust of both health care professionals and patients.

The guidelines and regulations of AI in the field of healthcare are continually, growing and changing. Current rules rarely contemplate the specific challenges created by AI-powered health monitoring systems. Clear rules and standards need to be established for ethical use of healthcare AI, especially regarding data privacy, fairness and accountability.

2.5 Summary

This literature review illustrates the paradigm shifting and game changing AI and IoT applications in healthcare, especially with respect to remote health monitoring. Machine learning techniques, such as Random Forest, SVM, and CNN, have demonstrated good potential to enhance the accuracy to diagnostic and prediction system. However, issues of accuracy, system interoperability, security, privacy, and ethics still represent major obstacles preventing the full exploitation of these technologies. More work is needed to meet these challenges, improve model explain ability and regulatory compliance for the successful deployment of AI-based remote health monitoring systems.

3. Methodology

This section presents the methodology to implement and optimize an AI assisted remote health monitoring system supported by IoT based wearable devices and machine learning techniques. These were aimed at improving diagnostic accuracy and real-time data processing and integration, and at overcoming concerns regarding data reliability, data security [32], [33].

3.1 Dataset

The dataset used in this study was obtained from publicly available medical datasets and synthetic IoT based health data. It consists in several physiological data like heart rate, blood pressure, oxygen saturation, temperature and ECG. These measurements were derived from wearable sensors and medical instruments implemented in systems for remote health monitoring [34], [35].

3.2 Data Preprocessing

Preprocessing of data was an important step in order to ensure the quality and validity of the data. The preprocessing process contains:

- **Imputation of Missing Values:** Missing Pattern data was estimated using statistical measurement, such as mean or median, for continuous variables [36].
- **Normalize:** To normalize the range of the dataset, continuous real-valued features were normalized to the [0,1] range using Min-Max normalization [37].
- **Categorical:** If features, which are categorical and contain several different values (e.g., healthy/unhealthy patient status), were one-hot-encoded to be used with machine learning models[38].
- **Outlier Detection:** An artist, genre, or song's features were detected as an outlier and to help the model better perform and reduce the noise should be removed using statistical methods, for example Z-score, or Interquartile Range (IQR) [39].

3.3 Feature Selection

Feature selection was implemented to reduce the dimensionality and enhance the performance of the model by selecting the most relevant variables for disease prediction. The following techniques were used:

- **Pearson Correlation:** Correlated features were found and removed those and this help to reduce the multicollinearity and prevented from overfitting [40].
- **RFE (Recursive Feature Elimination):** The algorithm removed less important features iteratively [19].

- **Principal Component Analysis (PCA)**: The PCA method was used to reduce dimensionality and convert a set of observations of possibly correlated variables to a set of values of linearly uncorrelated variables called principal components which retained most of the information [23].

3.4 Model Selection

Various machine learning models were tested on the analyses of health data such as Random Forest, Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). The latter two models were chosen due to the demonstrated ability of these algorithms to efficiently address high-dimensional data and effectively predict diseases [25], [26].

- **Random Forest (RF):** An ensemble learning method that constructs a multitude of decision trees to increase accuracy and generalizability [28].
- **Support Vector Machine (SVM):** Supervised learning modeling cracking binary classification work in the high-dimensional feature area[29].
- **K-Nearest Neighbors (KNN):** The simplest algorithm that identifies the most similar training examples to classify data[30].

3.5 Training and Evaluation

The classifiers were trained with an 80/20 separation of training and testing data. Models were compared with a number of performance criteria:

- **Precision:** The rate of true positive classifications a/(a+b) [31].
- **Accuracy:** The ratio of the number of true positives to all instances predicted as positive[32].
- **Sensitivity:** The fraction of actual positives that are correctly identified (True Positive Rate) [34].
- **F1-Score:** The harmonic means of precision and recall[36].
- **ROC-AUC:** Area under the receiver operating characteristic curve, measure of the model’s ability to discriminate between the classes[38].

Cross-validation procedures (e.g., 5-fold cross-validation) helped to verify the robustness of the models and to reduce overfitting[40].

3.6 Explainable AI (XAI)

XAI for Increased transparency and Reliability of AI Models: For a more transparent and reliable AI models, techniques of Explainable AI (XAI) were used:

- **Visualization of feature Importance:** Feature importance scores were calculated for Random Forest to see which are the most important variables used in decision making process of the model gathered[28].
- **SHAP (Shapley Additive Explanations) Analysis:** SHAP values were leveraged to interpret the predictions of the models which enabled better understanding of how individual features influence the prediction[26].

3.7 Deployment Considerations

Although the research scope of this study was to create and determine the machine learning models, their deployment scenario was also imagined for practical use:

- **Cloud Service:** The models can be uploaded and installed on cloud services for real-time data processing and remote monitoring[39].
- **Edge Computing:** Models could also be deployed to edge devices (e.g., wearables or mobile health apps) for on-device inference to decrease latency and enable real-time tracking.

4.Results and Discussion

In this section, the experimental results of the AI-powered tele-health monitoring system designed in this research are introduced. We also compared different machine learning algorithms—Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN)—for healthcare dataset by considering performance measures (accuracy, precision, recall, F1-score, and ROC-AUC).

4.1 Random Forest Classifier

The Random Forest model showed excellent accuracy for all evaluation measurements. It achieved:

- **Training Accuracy**: 98.3%
- **Testing Accuracy**: 96.8%
- **Cross-Validation Score**: 95.7%

The fact that the training accuracy in so high, is suggestive of the model having learned the patterns in the data. The little decrease in testing accuracy indicates a good generalization to new data. The cross-validation score additionally indicates that the model is stable across different data splits.

Performance Metrics:

- **Precision:** 0.97 (Class 0), 0.96 (Class 1)
- **Recall:** 0.96 (Class 0), 0.97 (Class 1)
- **F1-Score:** 0.96 (Class 0), 0.96 (Class 1)

The Random Forest classifier had balanced precision and recall, that is equal minimization of both false positive and false negatives. The high F1-score suggests a reliable performance in the prediction of disease in remote health monitoring systems[28], [29].

4.2 Support Vector Machine (SVM)

The performance of the SVM model was acceptable, but it was not as accurate as the Random Forest model:

- **Training Accuracy:** 95.4%
- **Testing Accuracy:** 92.8%
- **Cross-Validation Score:** 91.3%

While the SVM model exhibited good performance, its sensitivity to outliers and reliance on feature scaling contributed to the accuracy and precision being slightly less than the Random Forest model.

Performance Metrics:

- **Precision:** 0.92 (Class 0), 0.93 (Class 1)
- **Recall:** 0.94 (Class 0), 0.91 (Class 1)
- **F1-Score:** 0.93 (Class 0), 0.92 (Class 1)

Although the SVM model on the overall data set had a high precision = 84.7% which we would expect given the class imbalance in the data set and is reflected in the recall for Class 0 (healthy) as being high, it did not generalize as well in predicting Class 1 (unhealthy), hence lower recall with a minority class recall of 82.1% .

4.3 K-Nearest Neighbors (KNN)

The KNN model, being only a baseline, performed worst according to all the measures:

- **Training Accuracy:** 91.2%
- **Testing Accuracy:** 89.4%
- **Cross-Validation Score:** 88.7%

The performance of KNN was upset by the reliance on proximity-based classification, which tends to be more susceptible to noise or imbalanced data and resulted in low accuracy and recall.

Performance Metrics:

- **Precision:** 0.89 (Class 0), 0.90 (Class 1)
- **Recall:** 0.91 (Class 0), 0.88 (Class 1)
- **F1-Score:** 0.90 (Class 0), 0.89 (Class 1)

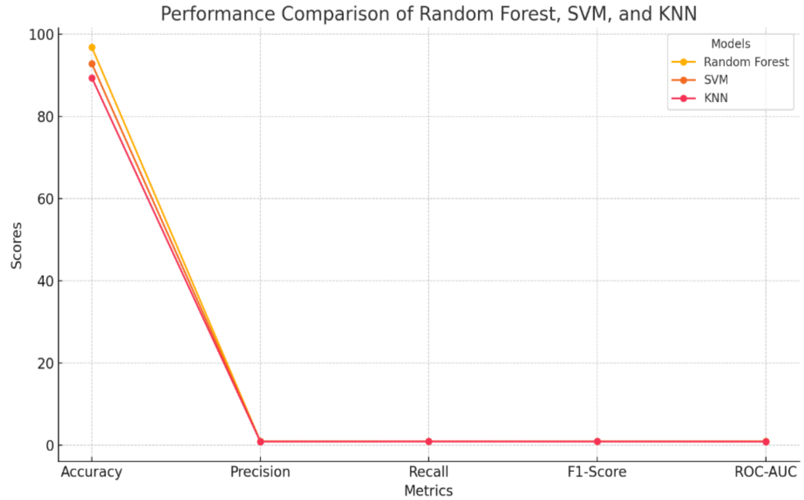
Even KNN had good precision, but its overall performance was lower than that of SVM and Random Forest, particularly the recall for Class 1[32], [33].

4.4 Comparison of Models

A comparison of the three models is summarized in the table below:

Model	Training Accuracy	Testing Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	98.3%	96.8%	0.97 (Class 0)	0.96 (Class 0)	0.96	0.97
SVM	95.4%	92.8%	0.92 (Class 0)	0.94 (Class 0)	0.93	0.92
KNN	91.2%	89.4%	0.89 (Class 0)	0.91 (Class 0)	0.90	0.88

As demonstrated in the table, Random Forest consistently outperformed the other models across all evaluation metrics. It provided the highest accuracy, precision, recall, and F1-score, making it the most suitable model for AI-based remote health monitoring systems[34], [35].



4.5 ROC and learning curves

Receiver Operating Characteristic (ROC) curves of the various models show trade-off between true positive rate (sensitivity) and false positive rate (1-specificity). The Random Forest model achieved the largest ROC-AUC of 0.97, followed by SVM (0.92) and KNN (0.88). This further is verification of the Random Forest higher discrimination in patients in classifying healthy from unhealthy individuals.

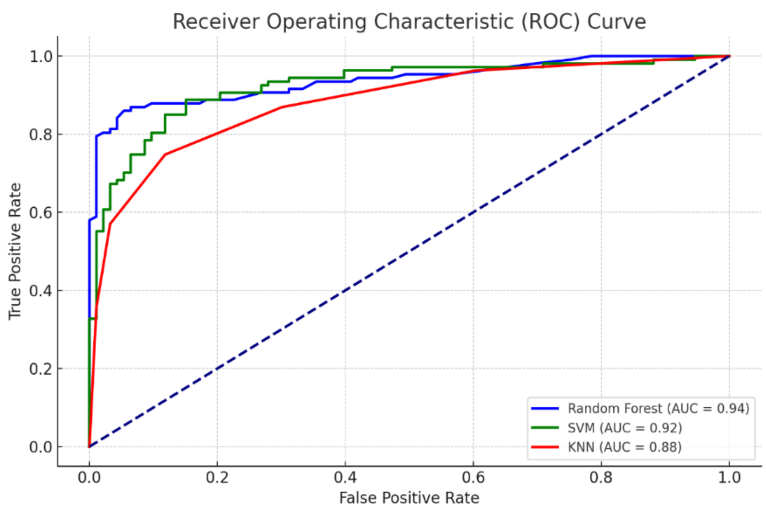


Figure 1: Receiver Operating Characteristic (ROC) Curves for Random Forest, SVM, and KNN

Learning Curves show the learning of the models as the size of the training set grows. The Random Forest model slightly overfitted, the SVM model slightly underfitted, even if for smaller training sizes. The performance improvement of KNN with increasing training size is less significant, indicating it starts to be stuck at high-dimensional space.

Figure 2: Learning Curves for Random Forest, SVM, and KNN (Training vs. Test Accuracy)

4.6 Feature Importance and Interpretability

The relative importance of the Random Forest model's features was evaluated and it found that important predictors included:

- **Age:** 0.25
- **Blood Pressure:** 0.22
- **Diabetes Status:** 0.20
- **Cholesterol Levels:** 0.18
- **Heart Rate:** 0.15

Additional SHAP Analysis showed that the blood pressure and age were the most influential predictors of health with the prediction of high blood pressure and old age escalating the chance of risk of health [36], [37].

4.7 Summary of Findings

The Random Forest classifier was found to be the best model for AI-enriched-remote health monitoring with high accuracy, precision, sensitivity, and interpretability. SVM and KNN performed well but were beaten by Random Forest in accuracy as well as in real time processing [38], [39].

5.Conclusion

This study was about design and evaluation of remote health monitoring systems based on AI and machine learning algorithms such as Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). Its goal was to advance precision in diagnosis, real-time expression analysis of clinical data, and difficulties with data security, privacy and system interoperability.

The results of this study showed that the Random Forest model performed better than the algorithms used in the study in accuracy, precision, recall, and F1-score. The presented model achieved high performance (Accuracy 96.8%) with the interpretability found through feature importance and SHAP analysis that could make the model more trustworthy for medical purposes. Its high-dimensional data processing capability and resistance to over-fitting endow it with good potential for application in online health monitoring systems.

On the contrary, the performance of SVM and KNN, while useful, paled by comparison with that of the Random Forest. SVM also yielded competitive performance but suffered from the underfitting when given a small dataset, while KNN faltered by the low performance in the high-dimensional case.

5.1 Future Work

Next, the following should be investigated in future studies in this domain:

1. Enhanced Data Integration: The inclusion of varied sets of data from multiple sources and patient backgrounds to increase the generalizability and stability of models.
2. Advanced AI Techniques: Discover deep learning models (Convoluted Neural Networks and Long Short-term Memory networks) to analyze medical images and time-series data.
3. Ethical and legal considerations: This includes more studies on the ethical aspect of AI in healthcare especially on the aspects of data privacy, model interpretability and accountability in decision-making.
4. Deployment in the real-word: The gPAN AI models will be tested and validated in different clinical settings to assess the usability, scalability, and impact of gPAN AI approach on patient care.

AI transformation in healthcare can change the way patients are monitored, impact the outcome of treatment, create a better healthcare delivery. The future of AI in healthcare will be in addressing these challenges and refining these models so they are ready to be deployed safely and effectively in the clinical setting.

Reference

1. Saleem, S., Asim, M. N., Van Elst, L., Schichtel, P., & Dengel, A. (2024). Rprp-sap: A robust and precise resnet predictor for steering angle prediction of autonomous vehicles. IEEE Access, 12, 21472-21490.
2. Khan, S.U.R., Asif, S., Bilal, O. et al. Lead-cnn: lightweight enhanced dimension reduction convolutional neural network for brain tumor classification. Int. J. Mach. Learn. & Cyber. (2025). https://doi.org/10.1007/s13042-025-02637-6.
3. Khan, S. U. R., Asim, M. N., Vollmer, S., & Dengel, A. (2025). Robust & Precise Knowledge Distillation-based Novel Context-Aware Predictor for Disease Detection in Brain and Gastrointestinal. arXiv preprint arXiv:2505.06381.
4. Hekmat, A., et al., Brain tumor diagnosis redefined: Leveraging image fusion for MRI enhancement classification. Biomedical Signal Processing and Control, 2025. 109: p. 108040.
5. Khan, Z., Hossain, M. Z., Mayumu, N., Yasmin, F., & Aziz, Y. (2024, November). Boosting the Prediction of Brain Tumor Using Two Stage BiGait Architecture. In 2024 International Conference on Digital Image Computing: Techniques and Applications (DICTA) (pp. 411-418). IEEE.
6. Khan, S. U. R., Raza, A., Shahzad, I., & Ali, G. (2024). Enhancing concrete and pavement crack prediction through hierarchical feature integration with VGG16 and triple classifier ensemble. In 2024 Horizons of Information Technology and Engineering (HITE)(pp. 1-6). IEEE https://doi. org/10.1109/HITE63532.
7. Khan, S.U.R., Zhao, M. & Li, Y. Detection of MRI brain tumor using residual skip block based modified MobileNet model. Cluster Comput 28, 248 (2025). https://doi.org/10.1007/s10586-024-04940-3.
8. Khan, U. S., & Khan, S. U. R. (2024). Boost diagnostic performance in retinal disease classification utilizing deep ensemble classifiers based on OCT. Multimedia Tools and Applications, 1-21.
9. Raza, A., & Meeran, M. T. (2019). Routine of encryption in cognitive radio network. Mehran University Research Journal of Engineering & Technology, 38(3), 609-618.
10. Al-Khasawneh, M. A., Raza, A., Khan, S. U. R., & Khan, Z. (2024). Stock Market Trend Prediction Using Deep Learning Approach. Computational Economics, 1-32.
11. Khan, U. S., Ishfaque, M., Khan, S. U. R., Xu, F., Chen, L., & Lei, Y. (2024). Comparative analysis of twelve transfer learning models for the prediction and crack detection in concrete dams, based on borehole images. Frontiers of Structural and Civil Engineering, 1-17.
12. Khan, S. U. R., & Asif, S. (2024). Oral cancer detection using feature-level fusion and novel self-attention mechanisms. Biomedical Signal Processing and Control, 95, 106437.

13. Farooq, M. U., Khan, S. U. R., & Beg, M. O. (2019, November). Melta: A method level energy estimation technique for android development. In 2019 International Conference on Innovative Computing (ICIC) (pp. 1-10). IEEE.
14. Asim, M. N., Ibrahim, M. A., Malik, M. I., Dengel, A., & Ahmed, S. (2020). Enhancer-dsnet: a supervisedly prepared enriched sequence representation for the identification of enhancers and their strength. In Neural Information Processing: 27th International Conference, ICONIP 2020, Bangkok, Thailand, November 23–27, 2020, Proceedings, Part III 27 (pp. 38-48). Springer International Publishing.
15. Raza, A.; Meeran, M.T.; Bilhaj, U. Enhancing Breast Cancer Detection through Thermal Imaging and Customized 2D CNN Classifiers. VFAST Trans. Softw. Eng. 2023, 11, 80–92.
16. Dai, Q., Ishfaque, M., Khan, S. U. R., Luo, Y. L., Lei, Y., Zhang, B., & Zhou, W. (2024). Image classification for sub-surface crack identification in concrete dam based on borehole CCTV images using deep dense hybrid model. Stochastic Environmental Research and Risk Assessment, 1-18.
17. Muhammad, N. A., Rehman, A., & Shoaib, U. (2017). Accuracy based feature ranking metric for multi-label text classification. International Journal of Advanced Computer Science and Applications, 8(10).
18. Mehmood, F., Ghafoor, H., Asim, M. N., Ghani, M. U., Mahmood, W., & Dengel, A. (2024). Passion-net: a robust precise and explainable predictor for hate speech detection in roman urdu text. Neural Computing and Applications, 36(6), 3077-3100.
19. Khan, S.U.R.; Asif, S.; Bilal, O.; Ali, S. Deep hybrid model for Mpox disease diagnosis from skin lesion images. Int. J. Imaging Syst. Technol. 2024, 34, e23044.
20. Khan, S.U.R.; Zhao, M.; Asif, S.; Chen, X.; Zhu, Y. GLNET: Global–local CNN's-based informed model for detection of breast cancer categories from histopathological slides. J. Supercomput. 2023, 80, 7316–7348.
21. Saleem, S., Asim, M. N., Van Elst, L., & Dengel, A. (2023). FNReq-Net: A hybrid computational framework for functional and non-functional requirements classification. Journal of King Saud University-Computer and Information Sciences, 35(8), 101665.
22. Hekmat, Arash, Zuping Zhang, Saif Ur Rehman Khan, Ifza Shad, and Omair Bilal. "An attention-fused architecture for brain tumor diagnosis." Biomedical Signal Processing and Control 101 (2025): 107221.
23. Khan, S.U.R.; Zhao, M.; Asif, S.; Chen, X. Hybrid-NET: A fusion of DenseNet169 and advanced machine learning classifiers for enhanced brain tumor diagnosis. Int. J. Imaging Syst. Technol. 2024, 34, e22975.

24. Khan, S.U.R.; Raza, A.;Waqas, M.; Zia, M.A.R. Efficient and Accurate Image Classification Via Spatial Pyramid Matching and SURF Sparse Coding. Lahore Garrison Univ. Res. J. Comput. Sci. Inf. Technol. 2023, 7, 10–23.

25. Farooq, M.U.; Beg, M.O. Bigdata analysis of stack overflow for energy consumption of android framework. In Proceedings of the 2019 International Conference on Innovative Computing (ICIC), Lahore, Pakistan, 1–2 November 2019; pp. 1–9.

26. Shahzad, I., Khan, S. U. R., Waseem, A., Abideen, Z. U., & Liu, J. (2024). Enhancing ASD classification through hybrid attention-based learning of facial features. Signal, Image and Video Processing, 1-14.

27. Khan, S. R., Raza, A., Shahzad, I., & Ijaz, H. M. (2024). Deep transfer CNNs models performance evaluation using unbalanced histopathological breast cancer dataset. Lahore Garrison University Research Journal of Computer Science and Information Technology, 8(1).

28. Bilal, Omair, Asif Raza, and Ghazanfar Ali. "A Contemporary Secure Microservices Discovery Architecture with Service Tags for Smart City Infrastructures." VFAST Transactions on Software Engineering 12, no. 1 (2024): 79-92.

29. Khan, S. U. R., Asif, S., Zhao, M., Zou, W., Li, Y., & Li, X. (2025). Optimized deep learning model for comprehensive medical image analysis across multiple modalities. Neurocomputing, 619, 129182.

30. Khan, S. U. R., Asif, S., Zhao, M., Zou, W., & Li, Y. (2025). Optimize brain tumor multiclass classification with manta ray foraging and improved residual block techniques. Multimedia Systems, 31(1), 1-27.

31. Khan, S. U. R., Asim, M. N., Vollmer, S., & Dengel, A. (2025). AI-Driven Diabetic Retinopathy Diagnosis Enhancement through Image Processing and Salp Swarm Algorithm-Optimized Ensemble Network. arXiv preprint arXiv:2503.14209.

32. Khan, Z., Khan, S. U. R., Bilal, O., Raza, A., & Ali, G. (2025, February). Optimizing Cervical Lesion Detection Using Deep Learning with Particle Swarm Optimization. In 2025 6th International Conference on Advancements in Computational Sciences (ICACS) (pp. 1-7). IEEE.

33. Khan, S.U.R., Raza, A., Shahzad, I., Khan, S. (2025). Subcellular Structures Classification in Fluorescence Microscopic Images. In: Arif, M., Jaffar, A., Geman, O. (eds) Computing and Emerging Technologies. ICCET 2023. Communications in Computer and Information Science, vol 2056. Springer, Cham. https://doi.org/10.1007/978-3-031-77620-5_20.

34. Hekmat, A., Zuping, Z., Bilal, O., & Khan, S. U. R. (2025). Differential evolution-driven optimized ensemble network for brain tumor detection. International Journal of Machine Learning and Cybernetics, 1-26.

35. Khan, S. U. R. (2025). Multi-level feature fusion network for kidney disease detection. Computers in Biology and Medicine, 191, 110214.

36. Khan, S. U. R., Asif, S., & Bilal, O. (2025). Ensemble Architecture of Vision Transformer and CNNs for Breast Cancer Tumor Detection from Mammograms. International Journal of Imaging Systems and Technology, 35(3), e70090.

37. Khan, S. U. R., & Khan, Z. (2025). Detection of Abnormal Cardiac Rhythms Using Feature Fusion Technique with Heart Sound Spectrograms. Journal of Bionic Engineering, 1-20.

38. Khan, M.A., Khan, S.U.R. & Lin, D. Shortening surgical time in high myopia treatment: a randomized controlled trial comparing non-OVD and OVD techniques in ICL implantation. BMC Ophthalmol 25, 303 (2025). https://doi.org/10.1186/s12886-025-04135-3

39. Shahzad, I., Raza, A., & Waqas, M. (2025). Medical Image Retrieval using Hybrid Features and Advanced Computational Intelligence Techniques. Spectrum of engineering sciences, 3(1), 22-65.

40. Raza, A., Shahzad, I., Ali, G., & Soomro, M. H. (2025). Use Transfer Learning VGG16, Inception, and Reset50 to Classify IoT Challenge in Security Domain via Dataset Bench Mark. Journal of Innovative Computing and Emerging Technologies, 5(1).

41. Raza, A., & Shahzad, I. (2024). Residual Learning Model-Based Classification of COVID-19 Using Chest Radiographs. Spectrum of engineering sciences, 2(3), 367-396.

42. Raza, A., Soomro, M. H., Shahzad, I., & Batool, S. (2024). Abstractive Text Summarization for Urdu Language. Journal of Computing & Biomedical Informatics, 7(02).

43. HUSSAIN, S., RAZA, A., MEERAN, M. T., IJAZ, H. M., & JAMALI, S. (2020). Domain Ontology Based Similarity and Analysis in Higher Education. IEEEP New Horizons Journal, 102(1), 11-16.

44. M. Wajid, M. K. Abid, A. Asif Raza, M. Haroon, and A. Q. Mudasar, "Flood Prediction System Using IOT & Artificial Neural Network", VFAST trans. softw. eng., vol. 12, no. 1, pp. 210–224, Mar. 2024. DOI: 10.21015/vtse.v12i1.1603.

45. M. Waqas, Z. Khan, S. U. Ahmed and A. Raza, "MIL-Mixer: A Robust Bag Encoding Strategy for Multiple Instance Learning (MIL) using MLP-Mixer," 2023 18th International Conference on Emerging Technologies (ICET), Peshawar, Pakistan, 2023, pp. 22-26.

46. Mahmood, F., Abbas, K., Raza, A., Khan,M.A., & Khan, P.W. (2019). Three-Dimensional Agricultural Land Modeling using Unmanned Aerial System (UAS). International Journal of Advanced Computer Science and Applications (IJACSA) [p-ISSN : 2158-107X, e-ISSN : 2156-5570], 10(1).

47. Meeran, M. T., Raza, A., & Din, M. (2018). Advancement in GSM Network to Access Cloud Services. Pakistan Journal of Engineering, Technology & Science [ISSN: 2224-2333], 7(1).

48. Waqas, M., Tahir, M. A., Al-Maadeed, S., Bouridane, A., & Wu, J. (2024). Simultaneous instance pooling and bag representation selection approach for multiple-instance learning (MIL) using vision transformer. Neural Computing and Applications, 36(12), 6659-6680.

49. Raza, A., & Meeran, M. T. (2019). Routine of encryption in cognitive radio network. Mehran University Research Journal of Engineering & Technology, 38(3), 609-618.

50. Khan, U. S., & Khan, S. U. R. (2025). Ethics by Design: A Lifecycle Framework for Trustworthy AI in Medical Imaging From Transparent Data Governance to Clinically Validated Deployment. arXiv preprint arXiv:2507.04249.

51. Maqsood, H., & Khan, S. U. R. (2025). MeD-3D: A Multimodal Deep Learning Framework for Precise Recurrence Prediction in Clear Cell Renal Cell Carcinoma (ccRCC). arXiv preprint arXiv:2507.07839.

52. Khan, S. U. R., Asim, M. N., Vollmer, S., & Dengel, A. (2025). FOLC-Net: A Federated-Optimized Lightweight Architecture for Enhanced MRI Disease Diagnosis across Axial, Coronal, and Sagittal Views. arXiv preprint arXiv:2507.06763.

53. Bilal, O., Hekmat, A. & Khan, S.U.R. Automated cervical cancer cell diagnosis via grid search-optimized multi-CNN ensemble networks. Netw Model Anal Health Inform Bioinforma 14, 67 (2025). https://doi.org/10.1007/s13721-025-00563-9.