International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

The role of Explainable AI in Digital Health using Explainable Artificial Intelligence and Machine Learning Techniques

Aerramsetty Srinivas [1], Shivendra*[2]

Submitted: 27/01/2024 **Revised**: 05/03/2024 **Accepted**: 13/03/2024

Abstract: Systematic literature reviews are crucial for understanding the current state of research and identifying gaps or areas for improvement. Machine learning methods hold great promise for predicting comorbidities and enhancing precision medicine. Using the PRISMA framework for our systematic review is an excellent approach as it provides a standardized method for conducting and reporting systematic reviews and meta-analyses, ensuring transparency and reproducibility. Searching multiple databases like Ovid Medline, Web of Science, and PubMed also helps ensure comprehensive coverage of relevant literature. Given the broad scope of our search terms, we will likely capture a wide range of studies focusing on disease coexisting conditions prediction using various machine learning techniques and traditional predictive modeling methods. This inclusivity can provide a comprehensive understanding of the current research landscape in this field. The advancement of explainable machine learning in coexisting conditions prediction holds immense potential for identifying previously unrecognized health needs. By leveraging sophisticated ML techniques alongside enhanced interpretability and explainability, healthcare professionals can gain deeper insights into the complex relationships between diseases and their comorbidities. These predictive models not only have the capability to identify known comorbidities but also have the potential to uncover novel associations and patterns that might have been overlooked using traditional methods. This means that patient groups previously not recognized as at risk for specific comorbidities could be identified, allowing for early intervention and personalized treatment strategies.

Keywords: *Digital health, Explainable AI, Machine Learning and Deep Learning, Precsion medical*

1. Introduction

As the population ages and medical advancements extend life expectancy, the burden of managing multiple chronic conditions is expected to rise substantially. This highlights the need for integrated, holistic healthcare approaches that consider physical and psychological well-being. Addressing coexisting conditions requires effective treatment and management strategies, preventive measures, and early detection. Predictive modeling techniques can be crucial in identifying individuals at risk for multiple conditions and guiding proactive interventions to mitigate their impact [1-2]. Furthermore, public health initiatives aimed at promoting healthy lifestyles, preventing chronic diseases, and addressing social determinants of health can help reduce the burden of coexisting conditions in the long term. Collaborative efforts across healthcare disciplines, policy-making bodies, and community organizations will be essential in addressing the multifaceted challenges of disease coexisting conditions [3-4]. Moreover, integrating explainable ML models into clinical practice can facilitate more informed decision-making by healthcare providers.

The financial burden of treating individuals with multiple long-term conditions is significant and projected to escalate in the coming years. The estimated cost of over £47 billion by 2035 in the UK alone underscores the economic impact of disease coexisting conditions on healthcare systems [5]. These costs encompass direct healthcare and indirect costs related to productivity loss and disability. The complex interactions between coexisting illnesses can complicate treatment and management, leading to worse health outcomes and diminished well-being [4]. By leveraging advanced analytics and predictive algorithms, healthcare providers can proactively identify individuals at risk for multiple conditions, tailor interventions to address their specific needs and optimize resource allocation within healthcare systems.

Additionally, integrating telemedicine, remote monitoring technologies, and digital health solutions can enhance coordinated care delivery for comorbid patients, reducing healthcare costs and improving outcomes. Addressing the challenges of disease coexisting conditions requires a multifaceted approach encompassing preventive strategies, care coordination, patient engagement, and ongoing research into effective treatment modalities [6-7]. Machine learning offers a powerful tool for addressing the challenge of disease coexisting conditions prediction and management. By leveraging large datasets, ML models can extract valuable insights from patient data [8-9]. One of the critical strengths of ML in coexisting conditions prediction is its ability to identify complex patterns and relationships. ML algorithms can uncover subtle interactions between diseases, risk factors, and patient characteristics by

[1]*Department of Mechanical Engineering, Vasavi College of Engineering, Hyderabad, India.*
[2]*Department of Computer Application, D.K College Dumraon, Buxar, Bihar, India*
Email id: srivastavashivendra29@gmail.com
Correspondence author: Shivendra

analyzing patient data, enabling more accurate predictions and personalized interventions.

Explainable AI (XAI) methods are crucial for ensuring the widespread adoption of machine learning (ML) models in healthcare, especially in areas like disease coexisting conditions prediction. By enhancing the interpretability and transparency of ML models, XAI methods provide clinicians with insights into why specific predictions are made, which is essential for building trust and confidence in these predictive models [10-11]. This transparency empowers healthcare providers to make informed decisions regarding patient care, treatment strategies, and preventive interventions [12]. XAI methods encompass a range of techniques aimed at elucidating the inner workings of ML models, including feature importance analysis, decision tree visualization, and model-agnostic approaches. By providing clinicians with actionable insights into how ML models arrive at their predictions, XAI methods bridge the gap between advanced analytics and clinical decision-making, facilitating the integration of ML into healthcare workflows.

Leveraging machine learning methods for predicting disease comorbidities holds tremendous potential. By accurately identifying individuals at risk for developing specific comorbid conditions, healthcare providers can tailor treatments and preventive strategies to each patient's unique needs, improving health outcomes and cost savings [13-14]. One of the critical advantages of ML in precision medicine is its ability to analyze large and diverse datasets, including clinical and genetic data, to uncover patterns and associations that may not be apparent through traditional analytical methods. By integrating these data sources and applying ML algorithms, healthcare providers can gain deeper insights into the underlying mechanisms driving disease comorbidities, enabling more personalized and effective interventions [15]. Furthermore, by providing healthcare providers with explainable ML models, clinicians can understand the rationale behind predictions and recommendations, fostering trust and confidence in these advanced analytical tools. This transparency is essential for successfully integrating ML into clinical practice and adopting personalized medicine approaches. By understanding how these models arrive at their predictions, clinicians can tailor interventions and care plans to address not only the primary disease but also its associated comorbidities, ultimately improving patient outcomes and quality of life.

2. Literature Review:

Systematic reviews play a crucial role in shaping practice guidelines by synthesizing the available evidence on a particular topic or intervention. By summarizing findings from multiple studies and assessing their quality, systematic reviews help identify the most effective and evidence-based approaches to patient care. This, in turn, enables clinicians to provide high-quality, standardized care grounded in the best available evidence. The methodological rigor of systematic reviews is paramount to their credibility and utility. Adhering to pre-established eligibility criteria and following a predefined methodological framework ensure the findings' transparency, reproducibility, and reliability. Systematic reviews minimize bias and objectively assess the available literature by systematically searching, appraising, and synthesizing the evidence.

The development of near real-time automation systems for detecting ventilator-associated pneumonia (VAP) represents a significant advancement in healthcare technology. These expert systems aim to improve the efficiency and accuracy of VAP detection, serving as valuable quality indicators for healthcare providers [16]. While near real-time automation systems have shown promise in streamlining the detection process and serving as quality indicators, their impact on improving the diagnostic accuracy of VAP has been limited. Despite their efficiency, these systems have yet to significantly enhance the ability to accurately diagnose VAP compared to traditional methods. However, it's worth noting that full compliance with preventive interventions has been shown to have a significant impact on reducing morbidity associated with VAP [17]. By implementing preventive measures such as strict infection control protocols and ventilator bundle strategies, healthcare facilities can reduce the incidence of VAP, decrease morbidity rates, and optimize resource utilization, including bed occupancy and ventilator use.

Digital health technologies offer many opportunities for personalizing medicine and improving healthcare delivery. Wearable biosensors, for instance, provide a convenient and non-invasive means of collecting real-time physiological data, enabling continuous monitoring of a patient's health status outside of traditional clinical settings. This constant data stream can offer valuable insights into patients' health trajectories, allowing for early detection of abnormalities and personalized interventions [18]. Telemedicine is another transformative digital health technology that has the potential to increase access to healthcare while reducing costs. By leveraging telecommunications technology, telemedicine enables remote consultations, diagnosis, and monitoring of patients, overcoming barriers such as geographical distance and limited access to healthcare providers. This improves patient convenience and healthcare efficiency, leading to cost savings and improved patient outcomes [19].

Artificial intelligence (AI) applications are crucial in leveraging the vast digital health data generated by wearable biosensors, telemedicine platforms, electronic health records, and other sources. By analyzing these data using advanced machine learning algorithms, AI can uncover patterns, trends, and correlations that may not be apparent through traditional methods. This enables the implementation of personalized treatment strategies tailored to individual patient needs, ultimately improving the effectiveness and efficiency of healthcare delivery [20]. Integrating digital health technologies and artificial intelligence can revolutionize healthcare by enabling personalized medicine, increasing access to care, and optimizing resource allocation.

The review presented by the authors [21-22] emphasizes the role of explainable artificial intelligence in fostering transparency, accountability, and trust within the healthcare domain. As healthcare increasingly relies on complex machine-learning models to inform clinical decision-making, it is crucial to ensure that these models are interpretable and explainable, allowing healthcare providers to understand the rationale behind predictions and recommendations. This underscores the ongoing challenges and opportunities in explainable artificial intelligence, particularly in healthcare, where the stakes are high, and the need for transparency is paramount. Overall, our review contributes valuable insights into the intersection of machine learning, digital health data, and precision medicine, highlighting both the progress made and the areas for future research and development. By fostering collaboration between researchers, healthcare providers, and technology developers, we can continue to harness the power of artificial intelligence to improve healthcare outcomes and enhance patient care [23].

3. Significance of study:

The systematic review provides a comprehensive overview of current research efforts, identifies gaps in knowledge, and lays the groundwork for future investigations. Systematic reviews play a vital role in advancing scientific understanding by collating and critically appraising the available evidence on a specific topic. In the case of disease coexisting conditions prediction, synthesizing the literature on ML methods allows researchers and healthcare practitioners to gain insights into state of the art, assess the performance of different ML models, and identify areas for improvement. This is particularly important in healthcare, where transparency and understanding of model predictions are essential for clinical decision-making and trust in AI-driven interventions. Overall, our systematic review fills a necessary gap in the literature and provides a valuable resource for researchers, clinicians, and policymakers in precision medicine and healthcare informatics. By synthesizing and critically appraising the existing evidence, our review advances knowledge and develops more effective strategies for managing disease coexisting conditions.

4. Materials and methods:

A systematic review has adopted a comprehensive approach by including papers that cover a broad spectrum of comorbidities without restrictions on the type of disease. Our review ensures inclusivity across diverse healthcare contexts, including rare, genetic, and chronic diseases. Focusing on the various machine learning algorithms used in the literature for disease coexisting conditions prediction allows Our to explore the breadth and depth of predictive modeling approaches in this field. ML techniques offer powerful tools for analyzing complex healthcare data and uncovering patterns and associations that may not be apparent through traditional statistical methods. This broad definition acknowledges the overlap between traditional statistical techniques and ML algorithms in the context of predictive modeling for disease coexisting conditions. Adopting a flexible approach ensures inclusivity and captures the full spectrum of predictive modeling methods used in the literature [24-25].

4.1: Extraction and analysis:

Using the PRISMA framework to report the findings of our systematic review ensures transparency and comprehensiveness in presenting our research methodology and results. Adhering to established guidelines like PRISMA enhances the credibility and reproducibility of our study, allowing readers to understand the process by which Our conducted our review and synthesized the available evidence. The information extracted from the selected articles covers a comprehensive range of factors. This detailed approach allows for a comprehensive synthesis of the literature and provides readers with a clear understanding of the scope and findings of our systematic review. Overall, by following the PRISMA framework and employing rigorous methods for literature search, study selection, and data extraction, our systematic review upholds high standards of quality and contributes valuable insights to the field of disease coexisting conditions prediction using machine learning methods.

4.2: Risk of bias and quality assessment:

PROBAST provides a structured framework for evaluating critical aspects of prediction model studies, including participants, predictors, outcome, and analysis, thereby facilitating a comprehensive assessment of study quality and applicability. Dividing the assessment into four domains (participants, predictors, outcome, and analysis) allows for a detailed evaluation of each aspect of the prediction models studied. Evaluating the applicability of the selected ML models to the target population, predictors, and outcomes further enhances the relevance and utility of our review findings. Understanding the prediction models' generalizability is essential for informing clinical decision-making and guiding future research directions.

5 Results:

5.1 Main findings:

The review process has been thorough and methodologically sound. The initial search across Ovid Medline, Web of Science, and PubMed, supplemented by manual searches of reference lists, yielded numerous articles for consideration. Removing duplicates and assessing eligibility based on predefined inclusion and exclusion criteria helped ensure that only relevant studies were included in the final review. They are assessing the full-text articles for eligibility, which allows for a more detailed evaluation of study characteristics and relevance to the research question. The identified studies cover a wide range of diseases and utilize various machine learning algorithms for predicting associated comorbidities, indicating the breadth and diversity of research in this field. Furthermore, providing details on the publication years and geographic distribution of the included studies enhances the transparency and comprehensiveness of our review findings. This information allows readers to contextualize the research landscape and understand potential variations in study methodologies and populations across different regions and periods.

5.2 Data sample size and types:

The variation in sample sizes across the 22 studies reflects the diversity of research settings and populations in disease coexisting conditions prediction using machine learning (ML) methods [26-27]. The use of retrospective cohort and case-control study designs, particularly with data sourced from electronic health records (EHRs), registries, and corporate databases, is consistent with the standard approach to conducting research in this area. These data sources provide rich and comprehensive information on patient demographics, medical history, and clinical outcomes, making them valuable resources for studying disease comorbidities [28]. The predominance of studies utilizing administrative and claim-based datasets, particularly those based on International Classification of Diseases, Tenth Revision (ICD-10) diagnoses, highlights the importance of leveraging existing healthcare data for predictive modeling. These datasets offer information on healthcare utilization, diagnoses, and procedures, allowing researchers to develop and validate ML models for disease coexisting conditions prediction [29-30].

5.3 ML methods and features:

The distribution of machine learning algorithms used for predicting comorbidities in the reviewed studies reflects the diversity of approaches employed in this field. Logistic regression and random forest emerge as the most commonly utilized algorithms, highlighting their popularity and effectiveness in disease coexisting conditions prediction. Logistic regression, a classic statistical method, is well-suited for binary classification tasks and offers interpretability, making it a natural choice for predicting comorbidities based on patient data. Random forest, a versatile ensemble learning technique, excels in handling complex datasets and capturing nonlinear relationships, making it a popular choice for predictive modeling in healthcare. Support vector machines and decision trees are also commonly employed ML algorithms for disease coexisting conditions prediction, offering different model complexity and interpretability strengths. Their inclusion in the reviewed studies underscores the importance of exploring multiple algorithmic approaches to achieve accurate and robust predictions. Their application in disease coexisting conditions prediction demonstrates the potential of deep learning in extracting meaningful insights from complex healthcare datasets. Probabilistic ML algorithms, such as Bayesian networks and Naive Bayes, offer a probabilistic framework for modeling uncertainty and capturing dependencies between variables, enhancing the interpretability and robustness of predictive models. This network-based approach provides a novel understanding of the interplay between different diseases and their associations.

The assessment of applicability is an essential aspect of evaluating the relevance and generalizability of studies on machine learning (ML) predictions of coexisting conditions. Our systematic review highlights that while most studies demonstrated a low concern regarding the applicability, a notable proportion 48 percent showed a high and unclear concern. The variability in data sources and recruitment methods used across the included studies can influence potential bias and the generalizability of findings. Studies that rely on interviews and questionnaires for participant recruitment may introduce biases and limitations related to self-reporting or recruiting specific population subsets. As a result, findings from these studies may have limited applicability to the broader population depicted by Fig 1 and Fig 2. It's essential to recognize the potential limitations of studies utilizing self-reported data and to interpret their findings within the context of these limitations.

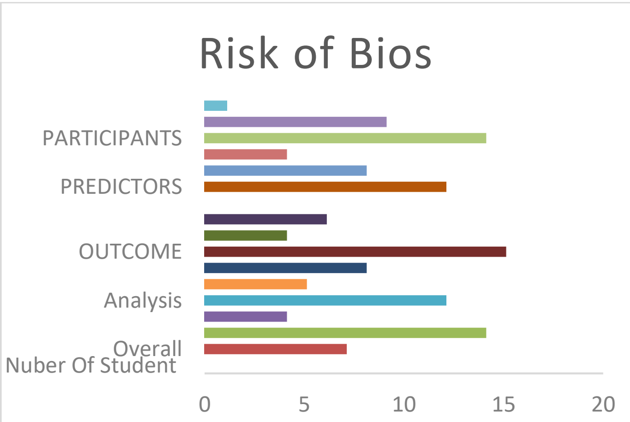

Fig 1: Results of the Risk of Bias

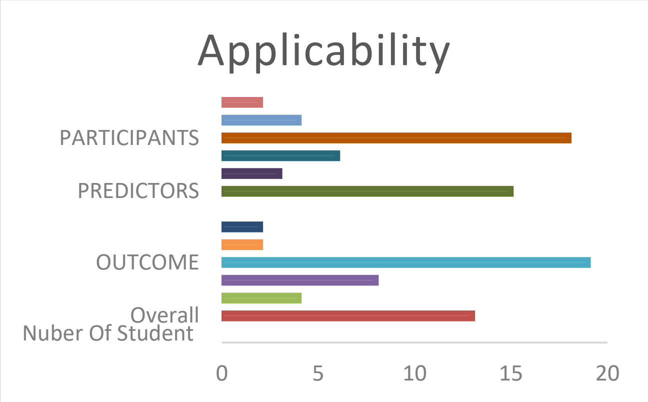

Fig 2: Results of the Applicability

6. Limitations and future work:

Sensitivity and Specificity are often paramount in medical diagnosis tasks, as they reflect the model's ability to correctly identify positive and negative cases. In future research, it would be beneficial to include a more comprehensive array of evaluation metrics and justify their selection based on the specific requirements of the predictive task. This approach would enhance the robustness and comprehensiveness of model evaluation and contribute to advancing best practices in machine learning research. The absence of AUC values in some studies can hinder the ability to reasonably compare model performance, especially when different evaluation metrics are used. Furthermore, not investigating whether included studies used other relevant metrics for assessing coexisting conditions prevalence prediction is another limitation that may affect the comprehensiveness of our review. In future research, addressing these limitations by ensuring consistent reporting of evaluation metrics, exploring the use of additional relevant metrics, and conducting comprehensive assessments of all developed machine learning models could enhance the validity and reliability of systematic reviews in this field.

7. Conclusion

The conclusion effectively summarizes the essential findings and implications of our systematic review on using artificial intelligence methods for predicting comorbidities in healthcare. By highlighting AI's potential to improve healthcare quality and cost-effectiveness, Our underscore the transformative impact of predictive modeling on patient care. Identifying a wide range of algorithms for coexisting conditions prediction reflects the diversity of approaches in this field while emphasizing the need for further development of explainable AI methods. This recognition underscores the importance of transparency and interpretability in AI-driven healthcare applications, particularly in clinical decision-making settings. There is potential for ML algorithms to identify unmet health needs and personalize medicine by incorporating them. By expanding the scope of predictive modeling to encompass a broader range of factors, healthcare providers can enhance the accuracy and relevance of coexisting conditions predictions, ultimately leading to more effective prevention and treatment strategies. Our conclusion emphasizes the transformative potential of transparent and explainable AI in revolutionizing disease prevention and treatment. By leveraging advanced analytical techniques and incorporating multidimensional data sources, AI-driven approaches have the power to improve patient outcomes and enhance healthcare delivery for all individuals.

Reference:

[1] .Abbas, Z. K., & Al-Ani, A. A. (2022). Anomaly detection in surveillance videos based on H265 and deep learning. International Journal of Advanced Technology and Engineering Exploration, 9(92), 910–922. https://doi.org/10.19101/IJATEE.2021.875907

[2] Abdullah, F., Javeed, M., & Jalal, A. (2021). Crowd Anomaly Detection in Public Surveillance via Spatio-temporal Descriptors and Zero-Shot Classifier. 4th International Conference on Innovative Computing, ICIC 2021, November.

[3] Chiranjeevi, K., and M. K. Tripathi. "Detection of Fruits Image Applying Decision Tree Classifier Techniques." Lecture Notes on Data Engineering and Communications Technologies 142 (2023).

[4] Pugazharasi, K., P. Kalaivani, J. Jayapriya, S. Kadhambari, and S. Mailvizhi. "Machine learning algorithms for predicting depression, anxiety and stress in modern life." In AIP Conference Proceedings, vol. 2587, no. 1. AIP Publishing, 2023.

[5] Tripathi, Mukesh Kumar, and Shivendra. "Neutroscophic approach based intelligent system for automatic mango detection." Multimedia Tools and Applications (2023): 1-23.

[6] Tripathi, Mukesh Kumar, M. Neelakantappa, Parikshit N. Mahalle, Shylesha V. Channapattana, Ganesh Deshmukh, and Ghongade Prashant. "Detection and Classification of Mango Fruit-Based on Feature Extraction Applying Optimized Hybrid LA-FF Algorithms." In Data-Centric Artificial Intelligence for Multidisciplinary Applications, pp. 177-185. Chapman and Hall/CRC.

[7] Müller, Oliver, Iris Junglas, Jan vom Brocke, and Stefan Debortoli. "Utilizing big data analytics for information systems research: challenges, promises and guidelines." European Journal of Information Systems 25 (2016): 289-302.

[8] Tripathi, Mukesh Kumar, Praveen Kumar Reddy, and Madugundu Neelakantappa. "Identification of mango variety using near infrared spectroscopy." Indonesian Journal of Electrical Engineering and Computer Science 31, no. 3 (2023): 1776-1783.

[9] Aleem, S., Nu Huda, R. Amin, S. Khalid, S. S. Alshamrani, and A. Alshehri. "Machine Learning

Algorithms for Depression: Diagnosis, Insights, and Research Directions. Electronics 2022, 11, 1111." (2022).
[10] Tripathi, Mukesh Kumar, Dhananjay Maktedar, D. N. Vasundhara, CH VKNSN Moorthy, and Preeti Patil. "Residual Life Assessment (RLA) Analysis of Apple Disease Based on Multimodal Deep Learning Model." International Journal of Intelligent Systems and Applications in Engineering 11, no. 3 (2023): 1042-1050.
[11] Lindemann, B., Maschler, B., Sahlab, N., & Weyrich, M. (2021). A Survey on Anomaly Detection for Technical Systems using LSTM Networks. Computers in Industry, 131, 1–14.
[12] Tripathi, Mukesh Kumar, M. Neelakantapp, Anant Nagesh Kaulage, Khan Vajid Nabilal, Sahebrao N. Patil, and Kalyan Devappa Bamane. "Breast Cancer Image Analysis and Classification Framework by Applying Machine Learning Techniques." International Journal of Intelligent Systems and Applications in Engineering 11, no. 3 (2023): 930-941.
[13] Chatterjee, Sheshadri, Ranjan Chaudhuri, and Demetris Vrontis. "Does data-driven culture impact innovation and performance of a firm? An empirical examination." Annals of Operations Research 333, no. 2 (2024): 601-626.
[14] Tripathi, Mukesh Kumar, M. Neelakantapp, Anant Nagesh Kaulage, Khan Vajid Nabilal, Sahebrao N. Patil, and Kalyan Devappa Bamane. "Breast Cancer Image Analysis and Classification Framework by Applying Machine Learning Techniques." International Journal of Intelligent Systems and Applications in Engineering 11, no. 3 (2023): 930-941.
[15] Trivedi, Naresh Kumar, Raj Gaurang Tiwari, Deden Witarsyah, Vinay Gautam, Alok Misra, and Ryan Adhitya Nugraha. "Machine Learning Based Evaluations of Stress, Depression, and Anxiety." In 2022 International Conference Advancement in Data Science, E-learning and Information Systems (ICADEIS), pp. 1-5. IEEE, 2022.
[16] Tripathi, Mukesh Kumar, CH VKNSN Moorthy, Vidya A. Nemade, Jyotsna Vilas Barpute, and Sanjeev Kumar Angadi. "Mathematical Modelling and Implementation of NLP for Prediction of Election Results based on social media Twitter Engagement and Polls." International Journal of Intelligent Systems and Applications in Engineering 12, no. 14s (2024): 184-191.
[17] Qasrawi, Radwan, Malak Amro, Stephanny VicunaPolo, Diala Abu Al-Halawa, Hazem Agha, Rania Abu Seir, Maha Hoteit et al. "Machine learning techniques for predicting depression and anxiety in pregnant and postpartum women during the COVID-19 pandemic: a cross-sectional regional study." F1000Research 11 (2022).
[18] Tripathi, Mukesh Kumar, M. Neelakantappa, Parikshit N. Mahalle, Shylesha V. Channapattana, Ganesh Deshmukh, and Ghongade Prashant. "Detection and Classification of Mango Fruit-Based on Feature Extraction Applying Optimized Hybrid LA-FF Algorithms." In Data-Centric Artificial Intelligence for Multidisciplinary Applications, pp. 177-185. Chapman and Hall/CRC.
[19] Chung, Jetli, and Jason Teo. "Mental health prediction using machine learning: taxonomy, applications, and challenges." Applied Computational Intelligence and Soft Computing 2022 (2022): 1-19.
[20] Tripathi, Mukesh Kumar, and Shivendra. "Improved deep belief network for estimating mango quality indices and grading: A computer vision-based Neutroscophic approach." Network: Computation in Neural Systems (2024): 1-29.
[21] Kumar, Prince, Shruti Garg, and Ashwani Garg. "Assessment of anxiety, depression and stress using machine learning models." Procedia Computer Science 171 (2020): 1989-1998.
[22] Tripathi, Mukesh Kumar, Sagi Hasini, Madupally Homamalini, and M. Neelakantappa. "Pothole Detection based on Machine Learning and Deep Learning Models." In 2023 International Conference on Advanced Computing Technologies and Applications (ICACTA), pp. 1-9. IEEE, 2023.
[23] Alsaleh, Mohanad M., Freya Allery, Jung Won Choi, Tuankasfee Hama, Andrew McQuillin, Honghan Wu, and Johan H. Thygesen. "Prediction of disease comorbidity using explainable artificial intelligence and machine learning techniques: A systematic review." *International Journal of Medical Informatics* (2023): 105088.
[24] Tripathi, Mukesh Kumar, and M. Neelakantappa. "Election Results Prediction Using Twitter Data by Applying NLP." International Journal of Intelligent Systems and Applications in Engineering 12, no. 11s (2024): 537-546.
[25] Priya, Anu, Shruti Garg, and Neha Prerna Tigga. "Predicting anxiety, depression and stress in modern life using machine learning algorithms." Procedia Computer Science 167 (2020): 1258-1267.
[26] Moorthy, CH VKNSN, Mukesh kumar Tripathi, Nilesh Pandurang Bhosle, Vishnu Annarao Suryawanshi, Priyanka Amol Kadam, and Suvarna Abhimunyu Bahir. "Investigating Advanced and Innovative Non-Destructive Techniques to Grade the Quality of Mangifera Indica." International Journal of Intelligent Systems and Applications in Engineering 12, no. 1 (2024): 299-309.
[27] 28. Albagmi, Faisal Mashel, Aisha Alansari, Deema Saad Al Shawan, Heba Yaagoub AlNujaidi, and Sunday O. Olatunji. "Prediction of generalized anxiety levels during the Covid-19 pandemic: A machine

learning-based modeling approach." Informatics in Medicine Unlocked 28 (2022): 100854.

[28] Roqué, Marta, Laura Martínez García, Ivan Solà, Pablo Alonso-Coello, Xavier Bonfill, and Javier Zamora. "Toolkit of methodological resources to conduct systematic reviews." F1000Research 9 (2020).

[29] Konduru, Preethi, Mukesh Kuamr Tripathi, Dipali Khairnar, Priyadarshini Patil, Madhavi Patil, and Ghongade Prashant. "Emerging Technology for Smart Farming in The Agriculture Domain: Application and Future Perspective." In 2023 International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT), pp. 88-93. IEEE, 2023.

[30] Lavanya P, Venkata, Mukesh Kumar Tripathi, Hemand E P, and Janjhyam Venkata Naga Ramesh. "Hyperspectral crop image classification via ensemble of classification model with optimal training." In Web Intelligence, no. Preprint, pp. 1-31. IOS Press.

[31] Shankar, KC Prabu, K. Deeba, and Amit Kumar Tyagi. "Machine Learning-Based Big Data Analytics for IoT-Enabled Smart Healthcare Systems." In AI-Based Digital Health Communication for Securing Assistive Systems, pp. 61-84. IGI Global, 2023.