Scholars Journal of Applied Medical Sciences
Abbreviated Key Title: Sch J App Med Sci
ISSN 2347-954X (Print) | ISSN 2320-6691 (Online)
Journal homepage: https://saspublishers.com

OPEN ACCESS

AI in Healthcare

AI in Cancer Detection: Early Identification of Esophageal and Skin Cancers in the United States

Pramod Chaudhary[1*]

[1]Indian Institute of Technology, Madras, India

DOI: https://doi.org/10.36347/sjams.2025.v13i02.040 | **Received:** 14.01.2025 | **Accepted:** 21.02.2025 | **Published:** 25.02.2025

***Corresponding author:** Pramod Chaudhary
Indian Institute of Technology, Madras, India

Abstract **Original Research Article**

Esophageal and skin cancers are among the most challenging malignancies, with early detection critical for improving survival rates and reducing healthcare costs. This paper explores the role of artificial intelligence (AI) in the early detection of these cancers in the United States, synthesizing methodologies from two key studies. For esophageal cancer, advanced machine learning techniques like Random Forest and XGBoost are employed to analyze multimodal data, including medical imaging, electronic health records (EHRs), and genomic profiles, achieving 92% accuracy in detecting early-stage cancer. For skin cancer, convolutional neural networks (CNNs) are used to analyze dermoscopic images, achieving an 87% accuracy in identifying malignant lesions. The study highlights the design and implementation of AI-driven models, covering data preprocessing, feature engineering, and evaluation metrics while addressing challenges such as class imbalance and overfitting. The results demonstrate AI's potential to enhance diagnostic accuracy, scalability, and accessibility, particularly in underserved areas. However, data privacy, algorithm interpretability, and regulatory compliance must be addressed to integrate AI into healthcare systems fully. This paper asserts that AI-driven diagnostics hold immense promise for revolutionizing cancer detection and calls for further research to overcome existing limitations while ensuring equitable access to these transformative technologies, ultimately improving patient outcomes and reshaping the landscape of cancer care.

Keywords: Artificial Intelligence (AI), Cancer Detection, Early Diagnosis, Esophageal Cancer, Skin Cancer, Machine Learning, Healthcare Innovation.

1. Introduction

1.1 Background

Cancer is a leading cause of death in the USA, with esophageal and skin cancers presenting unique diagnostic challenges. Esophageal cancer often remains undetected until advanced stages, resulting in poor survival rates of about 20% over five years (Al Amin *et al.*, 2025) [2]. Conversely, skin cancer, the most diagnosed malignancy in the USA, requires rapid detection to prevent morbidity and mortality. Traditional diagnostic techniques, including endoscopy and histopathology, are time-consuming, invasive, and inaccessible to many patients in underserved areas (Nasiruddin *et al.*, 2024) [9]. AI and machine learning have emerged as game-changers in medical diagnostics, offering unparalleled capabilities in analyzing complex datasets, including imaging and genomic data. Studies by Al Amin *et al.*, (2025) and Nasiruddin *et al.*, (2024) underscore the potential of AI-driven models in early cancer detection, paving the way for scalable and cost-effective solutions [2, 9].

1.2 Objective

This study aims to evaluate the transformative impact of artificial intelligence (AI) on cancer detection by synthesizing methodologies, outcomes, and insights from two pivotal studies focused on esophageal and skin cancers. This research aims to utilize advanced machine learning techniques, including convolutional neural networks (CNNs), that are used in this field. Ensemble models like Random Forest and XGBoost are used to create and validate AI-powered diagnostic tools. The goal is to improve the early detection of conditions, increase the accuracy of diagnoses, and make clinical workflows more efficient. Specifically, the study explores the application of AI in analyzing dermoscopic images for skin cancer detection and multimodal data integration— such as medical imaging, electronic health records (EHRs), and genomic profiles—for esophageal cancer diagnosis. The primary goal is to develop a comprehensive strategy for integrating AI into clinical practice. This includes addressing challenges like data accessibility, inconsistencies in diagnoses, and inequalities in healthcare.This research focuses on two common but difficult types of cancer, highlighting how AI can be a practical and affordable way to improve patient care. The goal is to minimize diagnostic mistakes and guarantee that people, especially in underserved and rural communities, have access to early cancer detection. Additionally, the study seeks to emphasize the ways in which AI can offer personalized treatment options, improve resource management, and ultimately revolutionize cancer care across the United States.

2. LITERATURE REVIEW

2.1. Esophageal Cancer Detection

Al Amin *et al.,* (2025) [2] conducted a groundbreaking study on applying AI algorithms for early esophageal cancer detection, leveraging a multimodal approach that integrated medical imaging, electronic health records (EHRs), and genomic profiles. The study utilized comprehensive datasets from reliable repositories such as the Surveillance, Epidemiology, and End Results (SEER) program, incorporating a wide range of variables, including demographic information (age, sex, race), clinical history (comorbidities, symptoms), risk factors (GERD, Barrett's esophagus), and diagnostic data (imaging results, histopathology, biomarkers). The AI models developed in this study demonstrated exceptional performance, achieving high accuracy in predicting early-stage esophageal cancer while significantly reducing false positives. We utilized several essential machine learning techniques, particularly Random Forest and XGBoost classifiers. These methods performed exceptionally well in classification tasks because they are great at dealing with complex, high-dimensional data. They're also capable of identifying the subtle patterns that can suggest early stages of malignancy. The research highlighted how AI could transform the way we diagnose esophageal cancer. It suggests that we could develop non-invasive, scalable, and affordable screening methods that can easily fit into existing clinical practices, especially for those at higher risk (Liu *et al.*, 2017) [7]. The use of machine learning techniques, such as Random Forest and XGBoost, has been widely recognized for their ability to handle complex datasets in healthcare. Recent studies, including Bhowmik *et al.,* (2024), have demonstrated the effectiveness of these algorithms in improving diagnostic accuracy and predictive performance in various medical applications, further supporting their utility in esophageal cancer detection [3]. The integration of multimodal data, including medical imaging, electronic health records (EHRs), and genomic profiles, has also been shown to significantly enhance early cancer detection. Bortty *et al.*, (2024) highlight the importance of advanced machine learning algorithms in optimizing risk prediction models, which aligns with the findings of this study in improving diagnostic accuracy for esophageal cancer [4].

2.2 Skin Cancer Detection

Nasiruddin *et al.,* (2024) [9] focused on optimizing skin cancer detection by applying convolutional neural networks (CNNs), a deep learning technique well-suited for image analysis. The study utilized the ISIC (International Skin Imaging Collaboration) dataset, which comprised over 1,000. Researchers worked with dermoscopic images classified into malignant and benign categories in their study. To boost the performance of their model, they applied several advanced preprocessing techniques. We focused on normalizing and resizing the images and using different augmentation techniques. These steps were necessary for addressing problems like class imbalance and reducing the chances of overfitting. The CNN model they created showed remarkable accuracy in detecting melanoma and other skin cancers, comparable to that of a dermatologist. This discovery highlights its promise as a dependable diagnostic tool. The research underscored the need to tackle class imbalance in the data, suggesting methods such as data augmentation and weighted loss functions to enhance the outcomes. These approaches significantly improved the model's capability to identify rare yet clinically essential cases. The proposed CNN model offers a way to automate the analysis of dermoscopic images, making it easier for dermatologists to make clinical decisions. This approach is particularly beneficial in regions with limited access to specialized care. The proposed CNN model offers a way to automate the analysis of dermoscopic images, making it easier for dermatologists to make clinical decisions. Advanced ML models, including deep learning algorithms, have improved early cancer risk prediction by identifying subtle imaging features, this promotes efficiency in the healthcare sector Bortty *et al.*, (2024) [4]. This approach is particularly beneficial in regions with limited access to specialized care. The study highlights the transformative potential of AI in improving diagnostic accuracy, reducing unnecessary biopsies, and enabling early intervention for skin cancer patients. Addressing challenges such as class imbalance and overfitting is critical in image-based diagnostics. Alam *et al.*, (2024) emphasize the importance of preprocessing techniques, including data augmentation and weighted loss functions, to improve model performance in skin cancer detection, which is consistent with the methodologies employed in this study [1].

2.3 Comparative Insights

While both studies underscore the transformative potential of artificial intelligence (AI) in cancer detection, they adopt distinct methodologies tailored to the unique diagnostic challenges of esophageal and skin cancers. Al Amin *et al.*, (2025) emphasized a multimodal data integration approach, combining medical imaging, electronic health records (EHRs), and genomic profiles to address the complexity of esophageal cancer [2]. This approach leverages diverse data sources to capture subtle patterns and predictive biomarkers often missed by traditional diagnostic methods. By utilizing advanced machine learning techniques such as Random Forest and XGBoost, the study demonstrated the ability to achieve high accuracy in early-stage cancer detection while minimizing false positives, highlighting the importance of integrating multiple data modalities for complex cancers.

In contrast, Nasiruddin *et al.,* (2024) focused on image-based diagnostics for skin cancer, employing convolutional neural networks (CNNs) to analyze dermoscopic images [9]. The study utilized the ISIC dataset, which contains over 1,000 images of skin lesions, and implemented advanced preprocessing techniques such as normalization and augmentation to enhance model performance. The CNN model achieved dermatologist-level accuracy in classifying skin cancer types, particularly melanoma, showcasing the power of AI in image analysis tasks. The research also addressed challenges such as class imbalance through techniques like data augmentation and weighted loss functions, ensuring robust performance across diverse skin lesion types.

Together, these approaches demonstrate the versatility of AI in addressing a wide range of diagnostic challenges. While Al Amin *et al.,* (2025) highlight the importance of multimodal data integration for cancers requiring comprehensive analysis of clinical, genetic, and imaging data, Nasiruddin *et al.,* (2024) illustrate the effectiveness of image-based AI models for cancers where visual diagnostics play a critical role [2, 9]. These complementary methodologies not only showcase the adaptability of AI across different cancer types but also provide a foundation for developing tailored AI solutions that can be integrated into clinical workflows. Combining insights from both studies, this research presents a holistic framework for leveraging AI to enhance diagnostic accuracy, improve accessibility, and ultimately transform cancer care.

3. METHODOLOGY

3.1 Data Collection and Preprocessing

The data collection and preprocessing steps are tailored to ensure the robustness, accuracy, and generalizability of the AI models developed. For **esophageal cancer**, the data sources are diverse and comprehensive, including imaging archives, electronic health records (EHRs), and genomic datasets. The integration of genomic data for personalized medicine requires robust preprocessing and feature engineering techniques. Pant *et al.,* (2024) discuss the importance of handling heterogeneous datasets and creating predictive variables to capture complex relationships, which is essential for ensuring the accuracy and generalizability of AI models in cancer detection [11]. These datasets provide a rich foundation for training AI models, encompassing demographic information, clinical history, risk factors, diagnostic data, and treatment outcomes. However, integrating such heterogeneous data presents challenges, including missing values, inconsistent formats, and the need for normalization to ensure compatibility across datasets. To address these issues, preprocessing steps involve normalization to standardize data scales, handling missing values through imputation techniques, and feature engineering to create predictive variables that capture the complex relationships between risk factors and cancer outcomes. These steps are critical to ensuring that the AI models can accurately identify patterns indicative of early-stage esophageal cancer, even in the presence of noisy or incomplete data.

The ISIC dataset serves as the primary data source for skin cancer, comprising over 1,000 dermoscopic images categorized into malignant and benign classes. The preprocessing pipeline for skin cancer detection is tailored to address challenges specific to image-based diagnostics, such as variability in image quality, class imbalance, and the risk of overfitting. Key preprocessing steps include image resizing to ensure uniformity, normalization to standardize pixel values, and augmentation techniques (e.g., rotation, flipping, and brightness adjustment) to expand the dataset and improve model generalization artificially. These steps are essential for enhancing the model’s ability to detect subtle visual patterns in skin lesions, particularly in cases where the dataset may be skewed toward certain classes. By addressing these challenges, the preprocessing pipeline ensures that the AI models are robust, reliable, and capable of achieving dermatologist-level accuracy in skin cancer detection.

3.2 Model Architectures

The study employed advanced machine learning models, including Random Forest and XGBoost, to classify cancer stages based on multimodal data for esophageal cancer detection. These models were chosen for their ability to handle complex, high-dimensional datasets integrating diverse data sources such as medical imaging, electronic health records (EHRs), and genomic profiles. The Random Forest algorithm, an ensemble learning method, was utilized to address the challenge of capturing intricate patterns and interactions within the data, which are critical for accurately predicting early-stage esophageal cancer. By constructing multiple decision trees and aggregating their outputs, Random Forest effectively reduced the risk of overfitting and improved generalization to unseen data. Similarly, the XGBoost algorithm, a gradient-boosting technique, was implemented to enhance predictive performance further. XGBoost excels in handling imbalanced datasets and optimizing complex classification tasks by sequentially building decision trees to correct errors from previous iterations. This approach proved particularly effective in reducing false positives and improving the precision of early cancer detection. Both models were trained on a comprehensive dataset that included demographic information, clinical history, risk factors, and diagnostic data, ensuring robust and generalizable predictions. Integrating these AI-driven models into clinical workflows addresses the limitations of traditional diagnostic methods, such as endoscopy and biopsy, which are often invasive, costly, and inaccessible to underserved populations. These models aim to improve early detection rates, reduce diagnostic errors, and enhance patient outcomes by providing a non-invasive, scalable, and cost-effective solution.

A convolutional neural network (CNN) architecture was implemented for skin cancer detection to classify dermoscopic images into multiple categories, including melanoma and benign lesions. The CNN model was designed with various convolutional and pooling layers to hierarchically extract features from input images, enabling the identification of subtle visual patterns indicative of skin cancer. Convolutional layers detected low-level features, such as edges and textures in the initial layers, while deeper layers captured higher-level features like lesion shapes and patterns. Pooling layers were incorporated to reduce the spatial dimensions of feature maps, thereby minimizing computational complexity and retaining the most salient information. Dropout layers were added to address the challenge of overfitting, which is common in deep learning models trained on limited datasets. These layers randomly deactivated a subset of neurons during training, forcing the model to learn more robust and generalizable features. The final layer of the CNN utilized a softmax activation function to output probability scores for each class, facilitating multi-class classification of skin lesions. Additionally, the model incorporated advanced preprocessing techniques, such as image normalization and augmentation, to enhance dataset diversity and mitigate class imbalance issues. The CNN model demonstrated dermatologist-level accuracy in classifying skin cancer, offering a reliable tool for automating the analysis of dermoscopic images. By addressing the limitations of traditional diagnostic methods, such as subjective visual inspection and variability in clinician expertise, this AI-driven approach provides a scalable solution for improving diagnostic accuracy and accessibility. The model's ability to detect subtle patterns imperceptible to the human eye further underscores its potential to support dermatologists in clinical decision-making, particularly in resource-constrained settings. Together, these model architectures highlight the transformative potential of AI in overcoming diagnostic challenges and enhancing cancer detection workflows.

3.3 Evaluation Metrics

To ensure the reliability and effectiveness of the AI models developed for esophageal and skin cancer detection, both studies employed a comprehensive set of evaluation metrics. These metrics were carefully selected to address the unique challenges of each diagnostic task and to provide a holistic assessment of model performance. For both esophageal and skin cancer detection, standard classification metrics such as accuracy, precision, recall, and F1-score were utilized. Accuracy measures the overall proportion of correct predictions, providing a general sense of model performance. However, given the imbalanced nature of medical datasets, where certain classes (e.g., malignant cases) may be underrepresented, precision and recall were prioritized to evaluate the model's ability to correctly identify positive cases while minimizing false positives and false negatives, respectively. The F1-score, as the harmonic mean of precision and recall, offered a balanced measure of the model's performance, particularly in scenarios where class imbalance could skew results. In addition to these metrics, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) was used to assess the model's ability to distinguish between classes across different probability thresholds. This metric is particularly valuable in medical diagnostics, as it provides insight into the model's discriminatory power and its ability to handle varying levels of diagnostic confidence.

For skin cancer detection, where the task involved not only classification but also the precise localization of lesions, additional metrics such as the Dice coefficient and Intersection over Union (IoU) were employed. The Dice coefficient measures the overlap between the predicted and ground truth segmentation masks, providing a quantitative assessment of the model's ability to accurately delineate lesion boundaries. Similarly, IoU evaluates the spatial agreement between predicted and actual regions of interest, offering a robust measure of segmentation accuracy. These metrics were critical for ensuring that the CNN model could reliably identify and localize skin lesions, a task that requires high precision in medical imaging applications.

4. RESULTS AND DISCUSSION

4.1 Performance Metrics

The AI models developed for esophageal cancer detection achieved impressive performance across key metrics. The accuracy of 92% indicates that the models correctly classified most cases, reflecting their ability to handle the complexity of multimodal data, including medical imaging, electronic health records (EHRs), and genomic profiles. The precision of 89% highlights the model's capability to minimize false positives, ensuring patients are not subjected to unnecessary invasive procedures or treatments. Meanwhile, the recall of 91% underscores the model's sensitivity in identifying actual positive cases, reducing the risk of missed diagnoses. This is critical for early-stage esophageal cancer, where timely intervention is paramount. The F1-score of 90%, balancing precision and recall, further confirms the model's robustness in handling imbalanced datasets and its reliability in clinical settings. These results demonstrate the potential of AI to address the limitations of traditional diagnostic methods, such as endoscopy and biopsy, by providing a non-invasive, scalable, and cost-effective solution for early cancer detection.

The CNN model for skin cancer detection also performed strongly, particularly in tasks involving image classification and lesion segmentation. The Dice coefficient of 0.85 and the Intersection over Union (IoU) of 0.78 indicate that the model achieved high levels of accuracy in delineating lesion boundaries, a critical requirement for precise diagnosis and treatment planning. These metrics reflect the model's ability to identify and localize skin lesions with a degree of precision comparable to that of dermatologists. Additionally, the precision of 87% demonstrates the model's effectiveness in minimizing false positives, ensuring that benign lesions are not misclassified as malignant. This is particularly important in reducing unnecessary biopsies and associated patient anxiety. The strong performance across these metrics highlights the potential of AI to augment dermatologists' expertise, particularly in resource-constrained settings where access to specialized care is limited.

4.2 Clinical Implications

The integration of artificial intelligence (AI) into cancer diagnostics holds significant promise for transforming healthcare delivery, particularly in the early detection and management of esophageal and skin cancers. Recent studies by Al Amin *et al.,* (2025) [2] and Nasiruddin *et al.,* (2024) [9] highlight several key clinical implications of this technology. Firstly, AI models such as Random Forest, XGBoost, and convolutional neural networks (CNNs) have shown superior performance compared to traditional diagnostic methods. By leveraging multimodal data, including medical imaging, electronic health records (EHRs), and genomic profiles, these models significantly reduce diagnostic errors, including false positives and negatives. This enhanced accuracy is crucial for early cancer detection, as timely and precise diagnoses can dramatically improve patient outcomes and survival rates. The clinical implications of AI in early cancer detection are profound, particularly in underserved areas. Hossain *et al.,* (2023) highlight the potential of AI-driven tools to improve diagnostic accuracy and patient outcomes, which aligns with the findings of this study in demonstrating the transformative impact of AI in esophageal and skin cancer detection.

Moreover, AI-driven diagnostic tools provide a scalable solution to address healthcare disparities, particularly in underserved and rural areas (Topol *et al.,* 2019) [5]. For instance, the CNN model developed for skin cancer detection can serve as a pre-screening tool in primary care settings, enabling healthcare providers to identify suspicious lesions and efficiently refer patients to specialists when needed. Similarly, AI algorithms for esophageal cancer detection can be integrated into telemedicine platforms, granting remote access to advanced diagnostic capabilities for patients in geographically isolated regions. Additionally, AI tools enhance cost-effectiveness by automating the analysis of complex datasets and medical images, thereby reducing the dependence on invasive and costly procedures such as biopsies and endoscopies. This not only lowers healthcare costs but also minimizes patient discomfort and the risk of complications. For example, utilizing AI to analyze dermoscopic images for skin cancer detection can decrease the need for unnecessary biopsies, while AI-driven risk stratification for esophageal cancer can optimize the use of endoscopic resources (Mckiney *et al.,* 2020) [6]. Overall, the integration of AI into cancer diagnostics represents a transformative step towards improving accuracy, accessibility, and affordability in cancer care.

4.3 Challenges

Integrating artificial intelligence (AI) into cancer diagnostics holds significant promise for transforming healthcare delivery, particularly in the early detection and management of esophageal and skin cancers. Recent studies by Al Amin *et al.,* (2025) and Nasiruddin *et al.,* (2024) highlight several key clinical implications of this technology [2, 9]. Firstly, AI models such as Random Forest, XGBoost, and convolutional neural networks (CNNs) have shown superior performance compared to traditional diagnostic methods. By leveraging multimodal data, including medical imaging, electronic health records (EHRs), and genomic profiles, these models significantly reduce diagnostic errors, including false positives and negatives. This enhanced accuracy is crucial for early cancer detection, as timely and precise diagnoses can dramatically improve patient outcomes and survival rates.

Moreover, AI-driven diagnostic tools provide a scalable solution to healthcare disparities, particularly in underserved and rural areas. For instance, the CNN model developed for skin cancer detection can serve as a pre-screening tool in primary care settings, enabling healthcare providers to identify suspicious lesions and efficiently refer patients to specialists when needed. Similarly, AI algorithms for esophageal cancer detection can be integrated into telemedicine platforms, granting patients remote access to advanced diagnostic capabilities in geographically isolated regions. Additionally, AI tools enhance cost-effectiveness by automating the analysis of complex datasets and medical images, thereby reducing the dependence on invasive and costly procedures such as biopsies and endoscopies. This lowers healthcare costs and minimizes patient discomfort and the risk of complications. For example, utilizing AI to analyze dermoscopic images for skin cancer detection can decrease the need for unnecessary biopsies. In contrast, AI-driven risk stratification for esophageal cancer can optimize the use of endoscopic resources. Integrating AI into cancer diagnostics is a transformative step toward improving accuracy, accessibility, and affordability in cancer care(Obermeyer *et al.*, 2016) [7].

5. Conclusion

Integrating artificial intelligence (AI) into cancer detection, particularly for esophageal and skin cancers, represents a transformative advancement in healthcare. The studies reviewed demonstrate that AI-driven models, such as Random Forest, XGBoost, and convolutional neural networks (CNNs), achieve remarkable accuracy in early cancer detection—92% for esophageal cancer and 87% for skin cancer. These models leverage multimodal data, including medical imaging, electronic health records (EHRs), and genomic profiles, to identify subtle patterns indicative of malignancy, significantly reducing diagnostic errors and improving patient outcomes. AI also addresses healthcare disparities by providing scalable, cost-effective solutions, particularly in underserved areas, through tools like telemedicine and automated image analysis. However, challenges such as data privacy, algorithm interpretability, and regulatory compliance must be addressed to integrate AI fully into clinical practice. Despite these hurdles, the potential of AI to revolutionize cancer diagnostics is undeniable, offering a pathway to earlier detection, personalized treatment, and more equitable access to care. Continued research and collaboration between technologists and healthcare providers are essential to overcome existing limitations and ensure that these innovations benefit all patients, ultimately reshaping the landscape of cancer care.

References

1. Alam, S., Hider, M. A., Al Mukaddim, A., Anonna, F. R., Hossain, M. S., Khalilor Rahman, M., & Nasiruddin, M. (2024). Machine Learning Models for Predicting Thyroid Cancer Recurrence: A Comparative Analysis. *Journal of Medical and Health Studies, 5(4)*, 113-129.
2. Al Amin, M., Liza, I. A., Hossain, S. F., Hasan, E., Islam, M. A., Akter, S & Haque, M. M. (2025). Enhancing Patient Outcomes with AI: Early Detection of Esophageal Cancer in the USA. *Journal of Medical and Health Studies*, 6(1), 08-27.
3. Bhowmik, P. K., Miah, M. N. I., Uddin, M. K., Sizan, M. M. H., Pant, L., Islam, M. R., & Gurung, N. (2024). Advancing Heart Disease Prediction through Machine Learning: Techniques and Insights for Improved Cardiovascular Health. *British Journal of Nursing Studies, 4(2)*, 35-50.
4. Bortty, J. C., Bhowmik, P. K., Reza, S. A., Liza, I. A., Miah, M. N. I., Chowdhury, M. S. R., & Al Amin, M. (2024). Optimizing Lung Cancer Risk Prediction with Advanced Machine Learning Algorithms and Techniques. *Journal of Medical and Health Studies, 5(4)*, 35-48.
5. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542(7639), 115-118.
6. Hossain, S. F., Al Amin, M., Liza, I. A., Ahmed, S., Haque, M. M., Islam, M. A., & Akter, S. (2023). AI-Based Brain MRI Segmentation for Early Diagnosis and Treatment Planning of Low-Grade Gliomas in the USA. *British Journal of Nursing Studies, 3(2)*, 37-55.
7. Liu, Y., Gadepalli, K., Norouzi, M., Dahl, G. E., Kohlberger, T., Boyko, & Stumpe, M. C. (2017). Detecting cancer metastases on gigapixel pathology images. arXiv preprint arXiv:1703.02442.
8. McKinney, S. M., Sieniek, M., Godbole, V., Godwin, J., Antropova, N., Ashrafian, H., ... & Shetty, S. (2020). International evaluation of an AI system for breast cancer screening. *Nature*, 577(7788), 89-94.
9. Nasiruddin, M., Hider, M. A., Akter, R., Alam, S., Mohaimin, M. R., Khan, M. T., & Sayeed, A. A. (2024). Optimizing Skin Cancer Detection in the USA Healthcare System Using Deep Learning and CNNs. *The American Journal of Medical Sciences and Pharmaceutical Research, 6(12)*, 92-112.
10. Obermeyer, Z., & Emanuel, E. J. (2016). Predicting the future—big data, machine learning, and clinical medicine. The New England Journal of Medicine, 375(13), 1216-1219.
11. Pant, L., Al Mukaddim, A., Rahman, M. K., Sayeed, A. A., Hossain, M. S., Khan, M. T., & Ahmed, A. (2024). Genomic Predictors of Drug Sensitivity in Cancer: Integrating Genomic Data for Personalized Medicine in the USA. *Computer Science & IT Research Journal, 5(12)*, 2682-2702.
12. Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature Medicine, 25(1)*, 44-56.