Cancer Care Nexus

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Keywords: Machine Learning, Deep Learning, Convolutional Neural Networks (CNN), Random Forest, Medical Diagnostics.

Abstract: The Cancer Care Nexus is an AI diagnostics plat- form for early cancer detection of breast, lung, skin, and blood cancer through machine learning and deep learning algorithms. The conventional diagnosis of cancer is invasive, time-consuming, and costly, making it inaccessible. The project fills these gaps with the application of Random Forest algorithms for text diagnosis and Convolutional Neural Networks (CNNs) for image diagnosis, which are efficient and accurate. Cancer Care Nexus offers a unified and easy-to-use interface, where health workers can input text or image and obtain reliable predictions, enabling multi- cancer diagnosis in a single platform. The system is scalable, adaptive, and privacy-friendly, providing secure processing of medical information. Future enhancement includes the expansion of cancer detection, model performance enhancement, and real- time predictive analysis integration. The project is a key milestone in AI-based healthcare making cancer detection faster, more accessible, and more accurate, which translates to improved patient outcomes in the world.

1 INTRODUCTION

Cancer is still one of the leading reasons for deaths across the world with millions of fresh cases diagnosed each year. According to the World Health Organization (WHO), cancer accounted for nearly 10 million deaths in the year 2020 alone and thus the urge for early and accurate detection methods is paramount. Early cancer detection significantly boosts the chances of survival by providing for timely and efficacious treatment. However, standard cancer detection methods, such as biopsies, imaging tests, and histopathological evaluation, are often invasive, tedious, costly, and call for specialized infrastructure available at all times in low-resource settings. Besides, types of cancers such as breast, lung, skin, and blood cancer require individual-specific diagnostic methods due to variance in symptoms, data structures, and clinical manifestations and thus rendering an integrated approach for multi-cancer detection unfruitful.

Cancer Care Nexus solves these problems by creating a single, AI-based diagnostic platform that employs machine learning and deep learning algorithms. This project com- bines several models to diagnose cancers of different types efficiently and accurately, providing a scalable and flexible solution for medical professionals. The system applies Random Forest models to text-based classification (breast and lung cancer) and Convolutional Neural Networks (CNNs) for image-based diagnosis (skin and blood cancer). By offering a single platform that supports both text and image inputs, Cancer Care Nexus makes cancer screening easier and more accessible to healthcare providers.

Conventional cancer diagnostic approaches are very much dependent on laboratory tests, imaging, and biopsies, with some drawbacks. Cancer diagnosis through biopsies can be several days to weeks long, hindering treatment decisions, while sophisticated imaging methods such as MRI and CT scans are expensive and require high-end equipment and skilled personnel, thus being out of reach for many in resource- poor areas. Moreover, tests such as biopsies and tissue extrac-tions are invasive, are uncomfortable, and also increase the chances of complications, with some tests requiring repeated analyses, further weighing down patients. Cancer detection is also type-dependent, with breast and lung cancer depending on patient history and clinical records, while skin and blood cancer diagnosis depends on image pattern recognition. Also, most

Rani, S. R., Praveen, T., Srihitha, G., Narayana, K. T. S. and Harika, N.
Cancer Care Nexus.
DOI: 10.5220/0013917900004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 4*, pages 623-630
ISBN: 978-989-758-777-1

regions, especially in developing nations, do not have trained oncologists, radiologists, and pathologists, leading to hurdles in early diagnosis. AI-based diagnostic tools are an apparent solution with automated, effective, and affordable screening, facilitating bridging of the gap in healthcare accessibility and early cancer detection.

Cancer Care Nexus circumvents the limitations of conventional cancer diagnosis by coupling sophisticated machine learning models into a single-platform, end-to-end diagnostic solution. For breast and lung cancer diagnosis, Random Forest models consume patient medical history, symptoms, and demographics and yield a non-invasive, affordable, and scalable solution for early-stage diagnosis. For skin and blood cancer diagnosis, Convolutional Neural Networks (CNNs) analyze high-resolution medical images, including dermatological scans and microscopic blood smear images, and detect subtle patterns and abnormalities to improve diagnostic accuracy over conventional manual inspection. The system provides a single, user-friendly interface that integrates both text- and image-based models, allowing healthcare practitioners to enter patient data and receive real-time diagnostic predictions. This reduces the need for multiple independent tools, accelerating the diagnostic process and enhancing accessibility, efficiency, and accuracy in cancer screening and early detection.

The use of Cancer Care Nexus has a number of benefits, and it is a revolutionary device for cancer screening. AI- driven models provide high diagnostic accuracy, improving the chances of early-stage detection, which raises treatment success rates and reduces mortality significantly. The platform combines breast, lung, skin, and blood cancer screening in one system, eliminating the use of individual screening devices and making the process cost-effective and efficient. By reducing dependence on expensive imaging techniques and specialist professionals, Cancer Care Nexus enhances accessibility, particularly in developing nations, and can be integrated into telemedicine services to enhance healthcare reach. Its explain- able and automated results allow non-specialists, including primary care doctors and community health workers, to con- duct preliminary screenings. Scalable in nature, the platform allows for future integration of new cancer types and improved AI models, ensuring continuous improvement with medical research developments. AI-driven automation also speeds up diagnosis while minimizing operational costs, making cancer screening cost-effective and accessible. The system has robust data security features, complying with HIPAA and GDPR standards to secure encrypted patient information. Moreover, its explainable AI models pinpoint the most significant factors driving predictions, ensuring transparency, clinical relevance, and trustworthiness, making Cancer Care Nexus a reliable decision-support system for doctors.

Khalid et al. suggested a deep learning-powered breast cancer detection model from computerized mammograms by utilizing feature selection methods like low-variance feature elimination, univariate feature selection, and recursive feature elimination for improved accuracy. Their research employed a dataset of 3,002 mammography images from 1,501 participants obtained from February 2007 to May 2015, testing six models of classification random forest, decision tree, k- nearest neighbors, logistic regression, support vector classifier, and linear support vector classifier B. N. Kumar et al. The outcome indicated high accuracy using less computational power, and hence the model is effective in the early detection of breast cancer. Combining MRI and CNN-based classification V. Sureshkumaret al, Khalid et al. presented an elastic solution that optimizes diagnostic processes while tackling computational issues. Their work adds to AI-assisted cancer diagnostics, paving the way for en- hanced predictive analytics and broader dataset generalization in the future.

Kabiraj et al.suggested a breast cancer risk prediction model based on ensemble machine learning methods, namely Random Forest and Extreme Gradient Boosting (XGBoost). Their research used a breast cancer dataset of 275 instances with 12 features to compare the predictive performance of these algorithms. The findings exhibited a 74.73% accuracy with Random Forest and 73.63% with XGBoost, indicating the promising potential of ensemble learning techniques in cancer risk prediction A. Jafari, et al. Their study is consistent with several studies focusing on the use of machine learning for breast cancer detection based on patient information and risk factors including family history, physical inactivity, psycho- logical stress, and differences in breast size. The application of machine learning in medical diagnosis has been effective in detecting patterns that might go unnoticed under conventional techniques, thereby rendering these models highly useful for the early detection of diseases. The research adds to the increasing use of AI-based cancer diagnosis, driving the construction of stronger predictive models with a view to improving clinical decision-making and patient outcomes.

B. S et al . suggested a machine learning-based lung cancer detection system to support radiologists in enhancing diagnostic accuracy and patient survival rates. The authors investigated several classification methods, such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree, Logistic Regression, Na¨ıve Bayes, and Random Forest, to identify lung cancer S. P. Maurya et al. The system utilized a multi-stage classification method, including data enhancement and segmentation by thresholding and marker-controlled watershed techniques R. Javed,et al. The research proved that machine learning greatly enhances the detection of lung cancer, with the Random Forest algorithm having the best accuracy of 88.5%. The results are consistent with studies showing the efficiency of AI-based diagnostic tools in medical imaging, especially in the detection of early-stage lung cancer P. Chaturvedi et al. Through the use of machine learning for automated classification, this method lightens the workload of radiologists and increases diagnostic accuracy. The research is an addition to current development of AI-driven healthcare solutions, advancing the development of more accurate and accessible lung cancer detection.

Agarwal et al.suggested a machine learning approach for the detection of lung cancer with an aim to minimize human error and maximize diagnostic accuracy with the help of automation. The research work used four machines learning algorithms Random Forest, Logistic Regression, Support Vector Machine, and Decision Tree S. P. Maurya et al, applied on a dataset of lung cancer in Google Colab, which offers a cloud platform that includes GPU support. The efficiency of these algorithms was measured across four main parameters: accuracy, recall, harmonic mean, and precision P. Chaturvedi et al.. The research emphasized the role of automated detection systems in reducing diagnostic errors and improving early detection of cancer. Their results confirm the findings of ongoing studies showing the capability of AI-based models in enhancing lung cancer diagnosis by facilitating quicker and more accurate screening. The comparative study of several algorithms helps achieve progress in machine learning technology in medical diagnosis and assists in developing cancer detection systems that are effective and scalable and are fit for medical use.

Shehta et al. suggested a deep learning-based method for the diagnosis of blood cancer, focusing on early detection to enhance treatment success rates and minimize mortality. Their research compared various deep learning architectures, such as ResNetRS50, RegNetX016, AlexNet, ConvNext, EfficientNet, Inception_V3, Xception, and VGG19, to determine the best model for efficient and accurate prediction of blood cancer. Of these, ResNetRS50 showed higher accuracy and speed with low error rates, and is a potential device for early detection of cancer. Their work aligns with continued attempts to apply deep learning for medical diagnosis since AI-based models continue to refine cancer screening through increased detection precision and less reliance on human examination. Using deep convolutional neural networks, their work helps develop computerized and scalable methods for blood cancer diagnosis that support the utilization of deep learning in enhancing clinical outcomes and early intervention plans.

Hemalatha et al. suggested an artificial neural network (ANN)-based method for the diagnosis of blood cancer based on sensor-generated physiological data. Their research em- ployed a sensor network to record important health parameters, such as cardiac and respiratory rates, body temperature, and blood pressure, which were then classified by an ANN . The model had a 92.1% diagnostic accuracy, showing that ANN-based systems can successfully diagnose blood cancer and learn to perform better as additional data are introduced. The current research fits within the recent stream of studies exploring AI-assisted cancer detection and the contribution of neural networks toward improving diagnostic accuracy at a reduced cost and dependency on comprehensive clinical testing. Through the use of sensor data and automated classification, this research adds to the creation of cost-effective, scalable, and real-time solutions for early detection of blood cancer, providing a potential alternative for more accessible and faster diagnosis in medical environments.

Akinrinade et al. suggested a deep learning approach for skin cancer detection, focusing on early diagnosis to enhance patient outcomes, especially in underserved areas. Their research mitigated issues like class imbalance and dataset constraints by employing methods such as transfer learning, data augmentation, and Generative Adversarial Networks (GANs) to boost model performance. The study used convolutional neural networks (CNNs) to scan dermoscopic images and utilized texture-based features to discriminate between malignant and benign lesions. It also experimented with sampling strategies and loss functions to enhance imbalanced dataset classification accuracy O. Akinrinade et al. It compared ensemble and hybrid models and identified the most efficient method of early detection of skin cancer. Their results are consistent with the recent progress in AI-based healthcare, illustrating that deep learning methods can highly improve skin cancer diagnosis accuracy and accessibility. By implementing such models on digital health platforms, the research helps advance the development of scalable and automated solutions for early cancer screening, diminishing reliance on conventional diagnostic approaches.

Kandhro et al. suggested an advanced deep learning technique for detecting skin cancer through upgrading the VGG19 pre-trained model using max pooling and dense layers. Different pre-trained models, such as VGG19, ResNet152v2, InceptionResNetV2, DenseNet201, ResNet50, and InceptionV3 were employed in their study to derive features from a skin lesion dataset that included malignant and benign samples. These features were then categorized based on machine learning algorithms including Linear Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Decision Tree (DT), and Logistic Regression (LR). The research proved that the use of the enriched VGG19 (E-VGG19) model A. Kandhro, et al with conventional classifiers greatly enhanced classification accuracy. Performance was assessed through recall, F1 score, precision, sensitivity, and accuracy, proving the efficacy of hybrid methods in enhancing skin cancer diagnosis. Their results help in the continued evolution of AI-driven automated diagnostic systems, offering clinicians more precise and effective means of early skin cancer detection, ultimately enhancing patient outcomes.

2 METHODOLOGY

2.1 Dataset Details

The Cancer Care Nexus system uses a heterogeneous and well-organized dataset for multi-cancer detection, including blood, skin, lung, and breast cancer. Each dataset is designed to fit the respective machine learning models applied for detection, providing high accuracy and reliability in classification. In the case of blood cancer detection, a dataset of 1,659 cancer and 3,389 normal images in .bmp format (each 450 × 450 pixels) is utilized as shown in Figure 1.They is high- resolution microscopic images that facilitate feature extraction using deep learning for detecting irregular blood cell shapes. Likewise, in the skin cancer dataset, there are 569 cancer and 235 normal images in .jpg format (each 194 × 259 pixels) so that Convolutional Neural Networks (CNNs) can classify malignant and benign skin lesions with precision as shown in Figure 2.

For the diagnosis of lung cancer, a structured dataset of 310 × 16 (.csv format) is employed with patient data, clinical features, and diagnostic labels. The breast cancer dataset also has a similar structured form, 570 × 6 (.csv format), enabling the use of machine learning classifiers like Random Forest and Logistic Regression for cancer detection at an early stage.

This collection of datasets provides a complete multi-modal analysis, combining text-based and image-based machine learning models for efficient and scalable cancer diagnosis to assist healthcare professionals in making quicker and more accurate predictions.

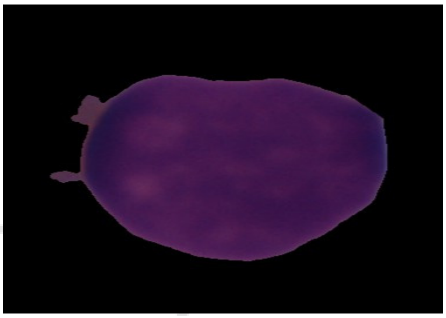

Figure 1: Blood cancer.

Figure 2: Skin cancer.

2.1.1 User Interaction & Data Input

The Cancer Care Nexus starts with user interaction, whereby the healthcare providers choose the cancer to be diagnosed breast, lung, skin, or blood using a friendly interface (UI). Based on the choice, the system calls for text-based input (breast and lung cancer) or image-based input (skin and blood cancer). The UI makes sure that the data is captured in the right format, reminding users if some information is incomplete or invalid. Valid user input is ensured through proper validation, and this avoids errors, allowing high-quality data to enter the system. The easy-to-use interface shown in Figure 3 makes navigation easier, enabling healthcare professionals to upload patient information and view diagnostic results in real time. The input is then chan- neled to the preprocessing module, where data is cleaned and standardized. This step is essential in minimizing human error, providing consistency, and facilitating smooth processing for the following detection models.

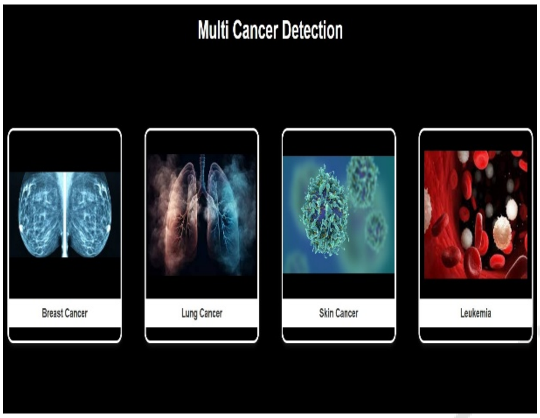

Figure 3: User interface.

2.1.2 Input Preprocessing

After the input data is received, the preprocessing module cleans and optimizes it to ensure proper classification. In the case of text data (lung and breast cancer), the system performs text normalization by eliminating inconsistencies like special characters, stop words, and formatting errors. The system then tokenizes the text, dividing it into meaningful parts for machine learning analysis. For visual data (blood and skin cancer), preprocessing includes scaling, normalizing, and image augmentation to improve the performance of the model. Normalization of images provides consistency in brightness, contrast, and scale, while image augmentation operations (including rotation and flipping) facilitate model generalization. These preprocessing techniques remove noise, improve pertinent features, and ensure the data is in a structured form prior to input into the detection models. By pre-processing data, the system reduces human interaction to a great extent, enhancing efficiency and ensuring high accuracy in diagnosis.

2.1.3 Models Used

The Cancer Care Nexus framework integrates different models, each defined for a specific type of cancer to offer accurate and rapid diagnosis. A Convolutional Neural Network (CNN) is utilized for image classification by the skin cancer detection module. The model contains three convolutional layers with 32, 64, and 128 filters (3×3 kernels), each followed by MaxPooling (2×2) to reduce spatial dimensions. After feature extraction, the model flattens data into a 1D vector of size 36,992 that is input to a dense layer with 512 units and a dropout layer (0.5) to prevent overfitting. The final sigmoid-activated dense layer enables binary classification to produce a total of 18,033,177 trainable parameters. For blood cancer detection, a more complex CNN architecture is employed, which consists of six convolutional layers having successively large filter sizes (32, 64, 128, and 256 filters). Each convolutional layer is followed by batch normalization to normalize training and MaxPooling (2×2) for dimensionality reduction.

The network comprises fully connected layers of 1,024 and 512 neurons, two dropout layers, and a sigmoid classification layer for binary output. This design results in 23,252,929 trainable parameters and hence makes the model effective to detect intricate patterns in blood smear images. To detect lung and breast cancer, random forest classifier is employed which is designed specifically for dealing with structured data. Instead of images, these models operate on numeric and categorical values of data present in tabular data sets in order to detect patterns in patients' history. The Random Forest algorithm builds numerous decision trees and averages multiple outputs, increasing classification robustness and reducing overfitting. By combining CNN-based image processing for skin and blood cancer and Random Forest-based structured data processing for lung and breast cancer, the Cancer Care Nexus system provides an end-to-end, multi-modal cancer detection solution. The hybrid approach enhances the classification's diagnostic accuracy, providing uniform classification for various cancers, and optimizing computational efficiency for real-world medical use.

2.1.4 Cancer Detection Model Execution

Following preprocessing, the system sends the data to the corresponding cancer detection model depending on the chosen type of cancer. In the case of breast and lung cancer, the system uses a Random Forest algorithm, which is very effec- tive for structured text data analysis in predictive classification. For skin and blood cancer, the system uses Convolutional Neural Networks (CNNs), which are particularly useful in image detection and detection of abnormalities in medical scans. All the models were trained on extensive datasets to identify unique cancer characteristics with high precision and recall rates. The models process the input data and output classification results, as shown in figure 5 forecasting whether the sample is cancerous or not. The output also comprises confidence scores, which express the model’s confidence level in its prediction. Through the use of sophisticated AI models, Cancer Care Nexus improves accuracy in diagnosis, lessening reliance on conventional, time-consuming screening techniques.

2.1.5 Integration & Result Processing

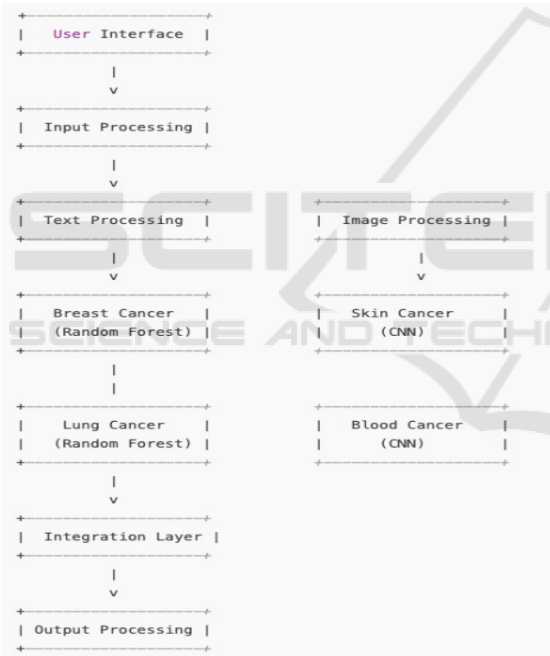

Figure 4: Proposed architecture.

After the predictions are made by the cancer detection models, the Integration Layer integrates and processes these outputs, which is done such that the data flows smoothly across various cancer detection modules. The system logically integrates and formats output, organizing them for clear presentation. It computes confidence scores to enable healthcare workers to gauge the validity of the diagnosis. The integration layer guarantees the detection process to be efficient and without errors, so that the end results are free from inconsistencies. It also merges multi-type cancer diagnoses into a single unified answer as shown in architecture in figure 4 which is essential for patients with risk for multiple cancers. The integration layer is critical to simplify, since healthcare workers are no longer required to manually decipher results from more than one system. Rather, all the diagnostic findings are displayed in one screen to give a unified and precise medical diagnosis.

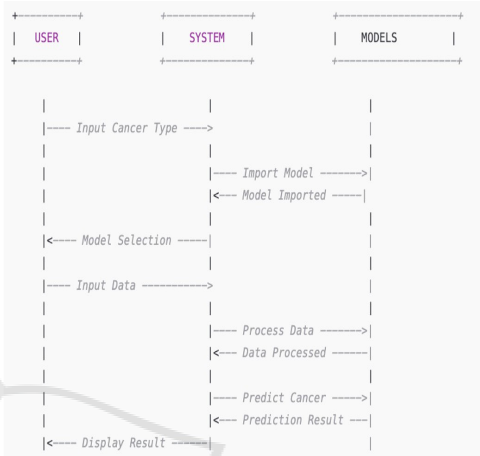

Figure 5: Proposed modules.

3 OUTPUT GENERATION & PRESENTATION

After the results are processed, the output processing mod- ule formats the diagnostic report for presentation in the user interface (UI). The results comprise cancer type classification, probability scores, and image-based diagnosis supporting visualizations. To make the information readable, the module structures and presents the information in a visual and intuitive fashion, facilitating easier interpretation by medical specialists. For borderline predictions, the system can recommend additional medical assessment, allowing clinicians to make better-informed decisions. The module also features a clinical recommendation area, providing suggestions for the next steps depending on AI analysis. The output processing guarantees the final results are trustworthy, properly structured, and readable, aiding healthcare professionals in providing timely and accurate diagnoses. This step closes the gap between AI- derived insights and actual clinical decision-making.

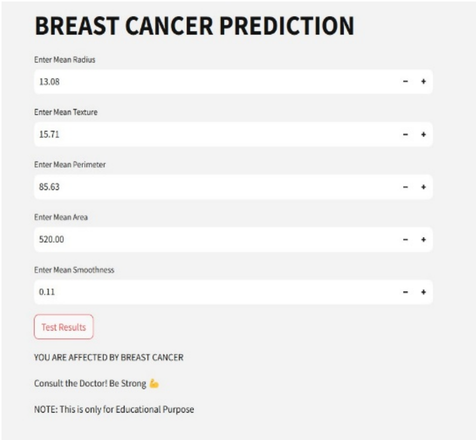

Figure 6: Breast cancer predition.

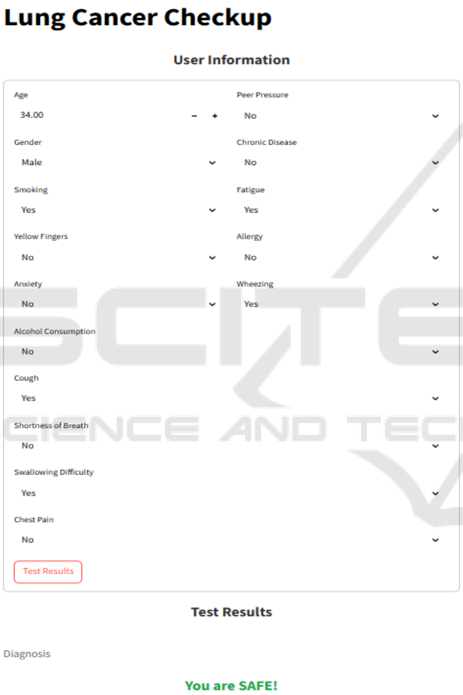

Figure 7: Lung cancer predition.

4 CONCLUSION AND FUTURE WORK

The Cancer Care Nexus system is an easy-to-use diagnostic platform combining machine learning algorithms for detection of breast, lung, skin, and blood cancers. As shown in figure 6, figure 7, figure 8. It uses random forest classifiers for text cancers and convolutional neural networks (CNNs) for image cancers with assured reliability. A common interface facilitates smooth interaction, with feedback from the user helping to improve it continuously. Patient data security features ensure privacy, and the scalability of the system makes it suitable for real-world applications. Future developments will involve cutting-edge deep learning methods, multimodal input data with text, images, and genomic information, and subtype-specific models for cancer. Real-time diagnostic functionality will enhance processing speed, and personalization through patient history and genetic information will improve predictions. Continuous learning will allow models to adapt, and cross modal data fusion will enhance analysis. Privacy enhancing methods such as federated learning will protect patient information, while international collaborations will increase datasets, making Cancer Care Nexus a stronger and wiser diagnostic tool. Figure 9 shows the lung cancer prediction.

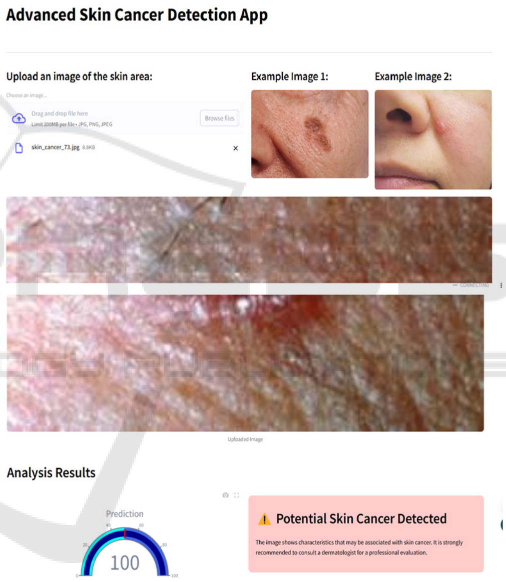

Figure 8: Skin cancer predition.

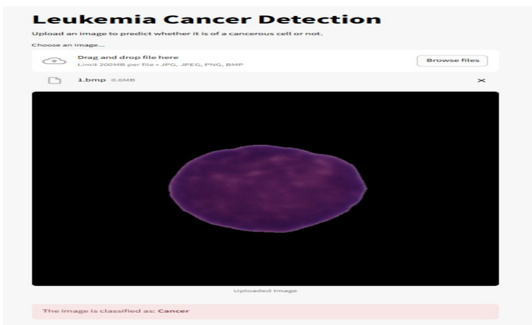

Figure 9: Lung cancer predition.

5 RESULTS

Cancer Care Nexus is an artificial intelligence-based cancer detection platform that is able to detect various types of can- cers through machine learning algorithms. The Breast Cancer Module uses a Random Forest Classifier for text analysis, with an accuracy of 93%, and the Lung Cancer Module uses the same algorithm for detecting lung cancer with an accuracy of 95%. For picture-based detection, the Skin Cancer Module uses a Convolutional Neural Network (CNN) to achieve 92% accuracy, while the Blood Cancer Module is also based on CNN and gives an 85% accuracy. Through these domain-specific models being integrated together, Cancer Care Nexus guarantees an end-to-end effective diagnostic process and early cancer detection, while helping healthcare experts to make proper clinical decisions.

REFERENCES

A. I. Shehta, M. Nasr, and A. E. D. M. El Ghazali," Blood cancer prediction model based on deep learning technique," Sci. Rep., vol. 15, no. 1, p. 1889, 2025.

A. Jafari, "Machine-learning methods in detecting breast cancer and related therapeutic issues: a review," Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization, vol. 12, no. 1, p. 2299093, 2024.

B. S, P. R, and A. B," Lung Cancer Detection using Machine Learning," in Proc. Int. Conf. Appl. Artif. Intell. Comput. (ICAAIC), Salem, India, 2022, pp. 539-543, doi: 10.1109/ICAAIC53929.2022.9793061.

B. N. Kumar, N. C. Gowda, B. J. Ambika, H. N. Veena, B. Ben Sujitha, and D. R. Ramani, "An efficient breast cancer detection using machine learning classification models," International Journal of Online & Biomedical Engineering, vol. 20, no. 13, 2024.

I. A. Kandhro, S. Manickam, K. Fatima, M. Uddin, U. Malik, A. Naz, and A. Dandoush, "Performance evaluation of E-VGG19 model: Enhancing real-time skin cancer detection and classification," Heliyon, vol. 10, no. 10, 2024.

I. A. Kandhro et al.," Performance evaluation of E-VGG19 model: Enhancing real-time skin cancer detection and classification," Heliyon, vol. 10, no. 10, 2024.

K. Hemalatha et al.," An Enhanced Analysis of Blood Cancer Prediction Using ANN Sensor-Based Model," Eng. Proc., vol. 59, no. 1, p. 65, 2023.

Khalid, A.; Mehmood, A.; Alabrah, A.; Alkhamees, B.F.; Amin, F.; AlSalman, H.; Choi, G.S. Breast Cancer Detection and Prevention Using Machine Learning. Diagnostics 2023, 13, 3113.

M. Adjouadi et al., "Classification of leukemia blood samples using neural networks," Annals of Biomedical Engineering, vol. 38, pp. 1473- 1482, 2010.

M. K. Monika, N. A. Vignesh, C. U. Kumari, M. N. V. S. S. Kumar, and E. L. Lydia, "Skin cancer detection and classification using machine learning," Materials Today: Proceedings, vol. 33, pp. 4266-4270, 2020.

O. Akinrinade and C. Du," Skin cancer detection using deep machine learning techniques," Intell.-Based Med., vol. 11, p. 100191, 2025.

O. Akinrinade and C. Du, "Skin cancer detection using deep machine learning techniques," Intelligence-Based Medicine, vol. 11, p. 100191, 2025.

P. Chaturvedi, A. Jhamb, M. Vanani, and V. Nemade, "Prediction and classification of lung cancer using machine learning techniques," in IOP Conference Series: Materials Science and Engineering, vol. 1099, no. 1, p. 012059, Mar. 2021, IOP Publishing.

R. Raina et al., "A systematic review on acute leukemia detection using deep learning techniques," Archives of Computational Methods in Engineering, vol. 30, no. 1, pp. 251-270, 2023.

R. Javed, T. Abbas, A. H. Khan, A. Daud, A. Bukhari, and R. Alharbey, "Deep learning for lungs cancer detection: a review," Artificial Intelligence Review, vol. 57, no. 8, p. 197, 2024.

S. Kabiraj et al.," Breast cancer risk prediction using XGBoost and random forest algorithm," in Proc. 11th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT), Kharagpur, India, Jul. 2020, pp. 1-6, doi: 10.1109/ICCCNT49239.2020.9225433.

S. Agarwal, S. Thakur, and A. Chaudhary," Prediction of Lung Can- cer Using Machine Learning Techniques and their Comparative Anal- ysis," in Proc. 10th Int. Conf. Reliability, Infocom Technol. Optim. (Trends Future Directions) (ICRITO), Noida, India, 2022, pp. 1-5, doi: 10.1109/ICRITO56286.2022.9965052.

S. P. Maurya, P. S. Sisodia, R. Mishra, and D. P. Singh, "Performance of machine learning algorithms for lung cancer prediction: a comparative approach," Scientific Reports, vol. 14, no. 1, p. 18562, 2024.

U. K. Lilhore, S. Simaiya, Y. K. Sharma, K. S. Kaswan, K. B. Rao, V. M. Rao, A. Baliyan, A. Bijalwan, and R. Alroobaea, "A precise model for skin cancer diagnosis using hybrid U-Net and improved MobileNet-V3 with hyperparameters optimization," Scientific Reports, vol. 14, 2024.

V. Sureshkumar, R. S. N. Prasad, S. Balasubramaniam, D. Jagannathan, J. Daniel, and S. Dhanasekaran, "Breast cancer detection and analytics us- ing hybrid CNN and extreme learning machine," Journal of Personalized Medicine, vol. 14, no. 8, p. 792, 2024.