International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 03 | March - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Deep Learning and Blockchain for Accurate Skin Cancer and Disease Detection

Dr.A. Suneetha[1], B. Niharika[2], A. Meghana[3], B.V. Kousalya[4] , B.Bhavyasri Pravallika[5]

[1]Associate Professor, Department of Computer Science and Engineering, KKR AND KSR INSTITUTE OF TECHNOLOGY AND SCIENCES (AUTONOMOUS), GUNTUR
[2]Student, Department of Computer Science and Engineering, KKR AND KSR INSTITUTE OF TECHNOLOGY AND SCIENCES (AUTONOMOUS), GUNTUR
[3]Student, Department of Computer Science and Engineering, KKR AND KSR INSTITUTE OF TECHNOLOGY AND SCIENCES (AUTONOMOUS), GUNTUR
[4]Student, Department of Computer Science and Engineering, KKR AND KSR INSTITUTE OF TECHNOLOGY AND SCIENCES (AUTONOMOUS), GUNTUR
[5]Student, Department of Computer Science and Engineering, KKR AND KSR INSTITUTE OF TECHNOLOGY AND SCIENCES (AUTONOMOUS), GUNTUR

---***---

Abstract - Skin cancer is a significant global health concern, primarily caused by excessive exposure to ultraviolet (UV) radiation. If not detected and treated early, skin cancer can spread to vital organs such as the lungs, brain, and liver, complicating treatment and reducing survival rates. Early detection is crucial for maximizing recovery chances and improving patient outcomes. This research proposes a deep learning-based application to enhance the accuracy and efficiency of skin cancer and disease prediction. This study combines Artificial Intelligence (AI) and blockchain technology to create a secure and efficient system. Patients can upload skin images, which are analysed by AI models, such as convolutional neural networks (CNNs) and logistic regression, to predict skin diseases, including cancer. Blockchain technology ensures data immutability, transparency, and security. Based on AI predictions, the system recommends verified doctors based on specialty and availability. This innovative approach aims to provide a reliable solution for early detection and treatment of skin cancer and related diseases.

***Key Words*:** Convolutional neural networks, DenseNet, ResNet, EfficientNet, blockchain, smart contracts.

1. INTRODUCTION

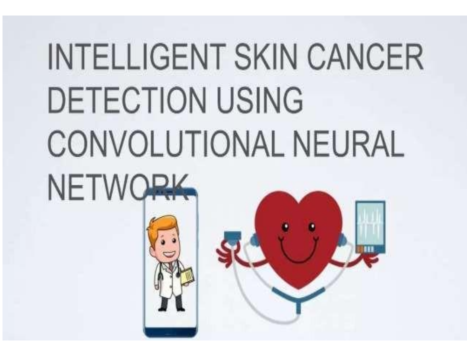

Fig.1 Detection of skin cancer

This research presents a blockchain-integrated AI system designed to predict skin diseases and recommend verified doctors, prioritizing data security, privacy, and trust. Through a user-friendly smartphone application, patients can upload images of their skin conditions. These images are analysed by advanced AI models, such as Convolutional Neural Networks (CNNs) and logistic regression, to predict the likelihood of skin diseases, including skin cancer, with high accuracy. Blockchain technology is employed to store immutable hashes of patient data, ensuring transparency and integrity, while the actual data is securely maintained on decentralized platforms like IPFS. This ensures both data security and patient control over their information. AI predictions and data records are logged on the blockchain, promoting fairness and accountability in decision-making. To further enhance healthcare delivery, the system recommends doctors based on blockchain-verified credentials, specialties, location, and availability. Patient reviews are securely stored on-chain to prevent tampering and maintain trust. Additionally, smart contracts automate key processes such as appointment booking streamlining workflows and reducing manual intervention. By combining the diagnostic power of AI with the security and transparency of blockchain, this system aims to improve accessibility, reliability, and trust in dermatological healthcare, ultimately contributing to better patient outcomes.

2. LITERATURE SURVEY

R. KARTHIK, et.al., (2024) In this article the authors presented about the study focused on improving the classification of skin lesions using advanced deep learning techniques. The researchers proposed a hybrid system combining two approaches: Swin Transformer, Dense Group Shuffle Non-Local Attention Network. By combining these methods, the system captures both the images and detailed features of skin images, resulting in accurate classification. **SUBHAJIT CHATTERJEE, et.al., (2024)** In this article the authors presented about a deep learning-based model is proposed for classifying skin lesions using dermoscopy images. It combines two pre-trained models to better understand different image features. Data balancing was done using techniques like data augmentation before training. The model works well for detecting seven types of skin conditions and is more accurate than earlier methods.

LUBNA RIAZ, et.al., (2023) In this article the authors presented about the study focuses on detecting skin diseases early by using a system that combines two technologies:

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 03 | March - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Convolutional Neural Networks (CNN) and Local Binary Pattern (LBP). CNNs help to find the patterns in images, while LBP looks at surface details of an image. The system combines the features from both methods to better identify different types of skin diseases.

H. L. GURURAJ, et.al., (2023) In this article the authors presented about the Skin cancer is rapidly spreading, and early detection is crucial for effective treatment. This study uses deep learning models, particularly CNNs like DenseNet169 and ResNet50, to classify skin lesions from the HAM10000 dataset. By applying undersampling and oversampling techniques, DenseNet169 outperformed ResNet50 in terms of accuracy and F1-score.

TOLGA CUKUR, et.al., (2022) In this article the authors presented about the study which introduces a deep clustering method using COM-Triplet loss to ensure balanced contributions from all classes. A GMM module generates pseudo-labels for unsupervised training, improving performance in various setups. The method outperforms current techniques, making melanoma detection more reliable. **PEDRO M. M. PEREIRA, et.al., (2022)** In this article the authors presented about the study which aims to improve melanoma detection by using both 2D color and 3D surface depth data with light-field cameras and deep learning. The model showed better accuracy and sensitivity compared to older methods. Adding 3D information helped classify skin lesions more effectively. Future work should focus on larger datasets and better imaging techniques.

JIANXIAO BIAN, et.al., (2021) In this article the authors presented about propose a multiview filtered transfer learning network, which exploits information from different image views by a novel multi-view weighing representation module and chooses useful source samples without negative effect from source domain by a filtered domain adaptation module. Classification done on Melanoma and Seborrheic Keratosis classification tasks.

KARL THURNHOFER-HEMSI, et.al., (2021) In this article the authors presented about a convolutional neural network along with multiple shifted versions of the test input image so that the shift vectors form a regular lattice. It takes the dataset from the HAM10000. Each shifted version is allocated to one of the networks of the ensemble. After that, the shifted versions of the test image are processed.

BELAL AHMAD, et.al., (2020) In this article the authors presented about a new framework by fine-tuning layers of ResNet152 and InceptionResNet-V2 models with a triplet loss function. In the proposed framework, first we learning the embedding from input images into Euclidean space by using deep CNN ResNet152 and InceptionResNet-V2 model. Second, we compute L-2 distances. Finally, classifying the input images using these L-2 distances.

REHAN ASHRAF, et.al., (2020) In this article the authors presented about a new system for detecting melanoma by focusing on specific Regions of Interest (ROIs) in skin images. Using an improved k-means algorithm, the system identifies areas likely containing melanoma cells. A CNN is then used to classify the extracted ROIs, addressing challenges like limited training data. Tested on the DermIS and DermQuest datasets, the system achieves high accuracy and full-image deep learning models.

3. PROPOSED METHODOLOGY

This research presents a blockchain-integrated AI system designed to predict skin diseases and recommend verified doctors, prioritizing data security, privacy, and trust. Through a userfriendly smartphone application, patients can upload images of their skin conditions. These images are analysed by advanced AI models, such as Convolutional Neural Networks (CNNs) and logistic regression, to predict the likelihood of skin diseases, including skin cancer, with high accuracy. Blockchain technology is employed to store immutable hashes of patient data, ensuring transparency and integrity, while the actual data is securely maintained on decentralized platforms like IPFS. This ensures both data security and patient control over their information. AI predictions and data records are logged on the blockchain, promoting fairness and accountability in decision-making. ResNet, DenseNet, and EfficientNet are popular deep learning frameworks for various tasks. ResNet uses skip connections to train very deep networks efficiently, making it suitable for image classification and object detection. DenseNet connects each layer to every other layer, ensuring better feature reuse and compactness, ideal for tasks with limited data or resources. EfficientNet balances depth, width, and resolution through compound scaling, providing state-of-the-art accuracy with fewer parameters, making it perfect for highperformance and mobile/edge deployments. Each framework is implemented in libraries like TensorFlow or PyTorch and can be selected based on accuracy, resource constraints, and task requirements.

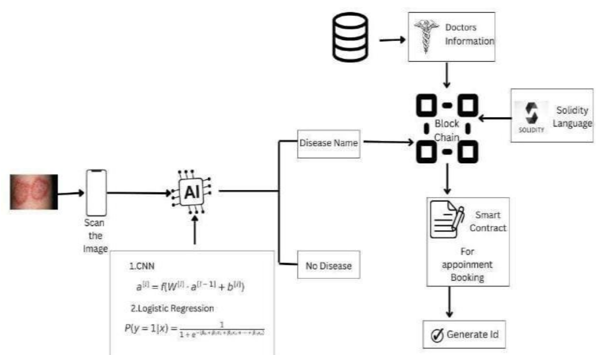

Fig.2 System Architecture

To further enhance healthcare delivery, the system recommends doctors based on blockchain-verified credentials, specialties, location, and availability. Patient reviews are securely stored on-chain to prevent tampering and maintain trust. Additionally, smart contracts automate key processes such as appointment booking streamlining workflows and reducing manual intervention. By combining the diagnostic power of AI with the security and transparency of blockchain, this system aims to improve accessibility, reliability, and trust in dermatological healthcare, ultimately contributing to better patient outcomes.

Algorithm Steps:

Upload: Patient uploads data → Stored securely.

Predict: AI analyzes → Results logged on blockchain.

Recommend: Doctor suggestions provided → Patient selects one.

Control: Data remains private → Access controlled by the patient.

Automate: Smart contracts handle payments and appointments.

4. RESULTS

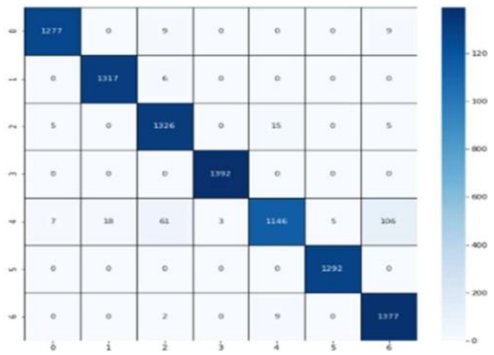

Fig.3 Results from the CNN model predictions

Sequential CNN Model: Sequential CNN model: This model includes standard convolution and pooling layers, resulting in a relatively simple calculation process. The computational complexity of a single CNN is generally O(n×m×k ×d), where n is the number of filters, m is the filter size, k is the number of input channels, and d is the network depth.

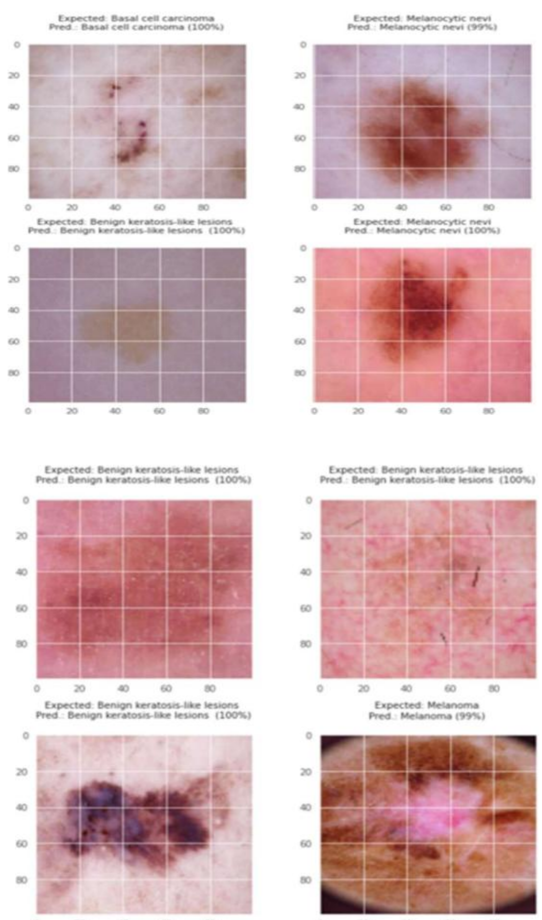

Fig.4 The image depicts instances where the model's predictions diverge from the actual skin lesion types.

Shows a few samples of misclassification or incorrect classification. The predicted result of the model is shown in the figure. An expected (original label of the class) and predicted (recognised by the model) class with an accuracy value is shown at the top of each test image. The percentage indicates how accurately the skin images have been classified. As depicted in the figure, third image from the top left corner, the original is Benign keratosis-like lesions, but the model had misclassified as Melanocytic nevi with a confidence score of 76%.

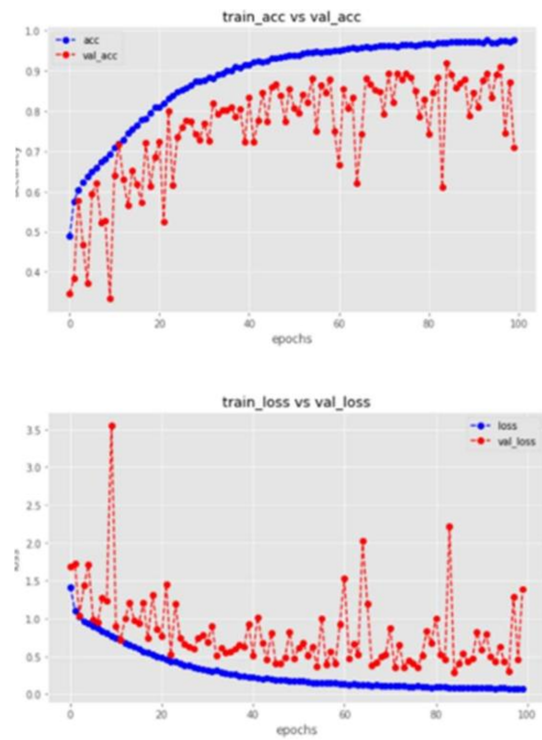

Fig.5 shows the learning curves for the CNN model.

Displays training and validation data's accuracy and loss curves. It shows the training history of the CNN model with 100 epochs. This is a crucial graphic to ensure the model gets better and more accurate with each passing epoch as it strives to maximize the goal function. The training accuracy and loss graph plot for the sequential CNN model is shown in the figures above. The accuracy and loss of a sequential CNN model fluctuate during training. The loss also declines at roughly the same rates.

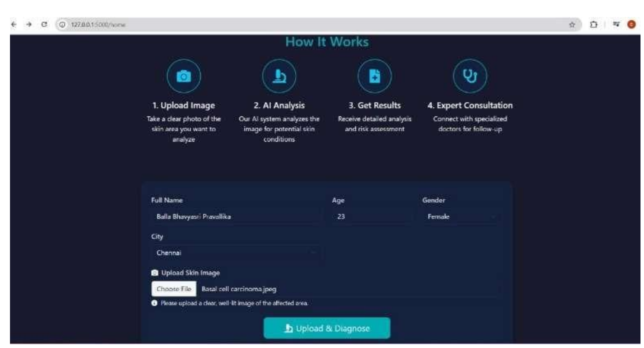

Fig.6 This page takes the customers details.

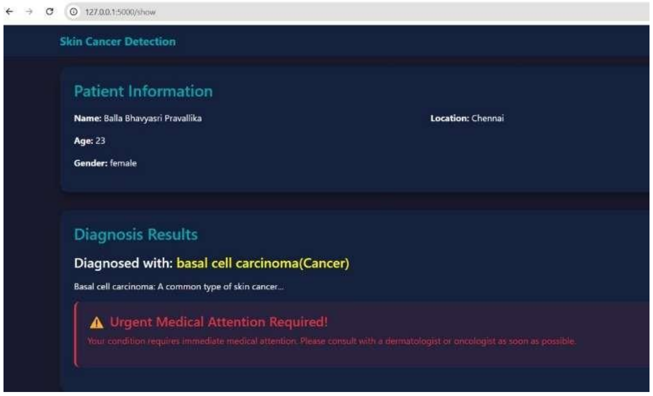

Fig.7 The Deep Learning model predicts the disease based on the image uploaded.

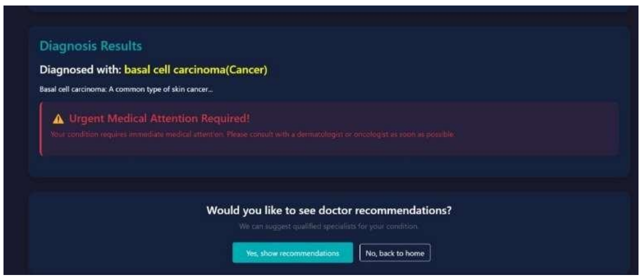

Fig.8 Diagnosis Results showing Doctor recommendation

The ROC curves show the performance of one model, tried on skin lesion classification: The Sequential CNN model. In the ROC curve, the Sequential CNN model (ROC curve) exhibits high performance with areas under the curve.

(AUC) around 0.99 to 1.00 for each class, indicating that the model is remarkably sensitive and specific.

CONCLUSION

Using blockchain technology in a skin disease and skin cancer prediction system, along with doctor recommendations, can solve important issues like data security, privacy, and trust. Blockchain ensures that patient data is safely stored and cannot be changed without permission. This gives patients control over their own information and helps keep their medical records private and secure. The AI system that predicts skin diseases uses advanced models like CNNs (Convolutional Neural Networks). Blockchain helps ensure that these predictions are accurate and that the AI system's decisions can be trusted. Smart contracts can also automate tasks like recommending doctors, booking appointments, and processing payments, making the system more efficient for patients and doctors. By using techniques like supervised and unsupervised deep clustering, the system becomes better at handling cases where there are fewer examples of certain skin diseases. Blockchain also keeps track of training data and model performance, which builds trust in the system's results. Overall, this approach makes the system more reliable and efficient, while giving patients control over their data. It creates a trustworthy environment for skin disease detection and cancer prediction, and helps improve healthcare services through technology. In the future we are going to extend this for more skin diseases like vitiligo, squamous cell carcinoma, albinism.

REFERENCES

[1]. R. KARTHIK, R. MENAKA, SHIVANSH ATRE, JAEHYUK CHO, AND SATHISHKUMAR VEERAPPAMPALAYAM EASWARAMOORTHY, "A Hybrid Deep Learning Approach for Skin Cancer Classification Using Swin Transformer and Dense Group Shuffle Non-Local Attention Network", IEEE Transactions, VOLUME 12, Page no:158040- 158051, 2024, **DOI**: 10.1109/ACCESS.2024.3485507

[2]. SUBHAJIT CHATTERJEE, JOON-MIN GIL, AND YUNG-CHEOL BYUN, "Early Detection of Multiclass Skin Lesions Using Transfer Learning-Based IncepX-Ensemble Model", IEEE Transactions, VOLUME 12, Page no: 113677- 113693, 2024, **DOI**:10.1109/ACCESS.2024.3432904

[3]. LUBNA RIAZ, HAFIZ MUHAMMAD QADIR, GHULAM ALI, MUBASHIR ALI, MUHAMMAD AHSAN RAZA, ANCA D. JURCUT AND JEHAD ALI, "A Comprehensive Joint Learning System to Detect Skin Cancer", IEEE Transactions, VOLUME 11, Page no: 79434 – 79444, 2023, **DOI:** 10.1109/ACCESS.2023.3297644

[4]. H. L. GURURAJ, N. MANJU, A. NAGARJUN, V. N. MANJUNATH ARADHYA AND FRANCESCO FLAMMINI, "DeepSkin: A Deep Learning Approach for Skin Cancer Classification", IEEE Transactions, VOLUME 11, Page no: 50205 – 50214, 2023, **DOI:** 10.1109/ACCESS.2023.3274848

[5]. SABAN ÖZTÜRK AND TOLGA ÇUKUR, "Deep Clustering via Center-Oriented Margin Free-Triplet Loss for Skin Lesion Detection in Highly Imbalanced Datasets", IEEE Transactions, VOLUME 26, Page no: 4679 – 4690, 2022, **DOI:**10.1109/JBHI.2022.3187215

[6]. PEDRO M. M. PEREIRA, LUCAS A. THOMAZ, LUIS M. N. TAVORA, PEDRO A. A. ASSUNCAO, RUI FONSECA-PINTO, RUI PEDRO PAIVA, AND SERGIO M. M. FARIA, Multiple Instance Learning Using 3D Features for Melanoma Detection", IEEE Transactions, VOLUME 10, Page no: 76296 - 76309, 2022, **DOI:** 10.1109/ACCESS.2024.3432904

[7]. JIANXIAO BIAN, SONG ZHANG, SHAOQIANG WANG, JIANRUI ZHANG1 AND JINCHANG GUO, "Skin Lesion Classification by Multi-View Filtered Transfer Learning", IEEE Transactions, VOLUME 9, Pageno:66052-66061,2021, **DOI:**10.1109/ACCESS.2021.3076533

[8]. KARL THURNHOFER-HEMSI, EZEQUIEL LÓPEZ-RUBIO, ENRIQUE DOMÍNGUEZ AND DAVID A. ELIZONDO, "Skin Lesion Classification by Ensembles of Deep Convolutional Networks and Regularly Spaced Shifting", IEEE Transactions, VOLUME 9, Page no: 112193 - 112205, 2021, **DOI:** 10.1109/ACCESS.2021.3103410

[9]. BELAL AHMAD, MOHD USAMA, CHUEN-MIN HUANG, KAI HWANG, M. SHAMIM HOSSAIN, "Discriminative Feature Learning for Skin Disease Classification Using Deep Convolutional Neural Network", IEEE Transactions, VOLUME 8, Page no: 39025 - 39033, 2020, **DOI:** 10.1109/ACCESS.2020.2975198

[10]. REHAN ASHRAF, SITARA AFZAL, ATTIQ UR REHMAN, SARAH GUL, JUNAID BABER, MAHEEN BAKHTYAR, IRFAN MEHMOOD, OH-YOUNG SONG AND MUAZZAM MAQSOOD, "Region-of-Interest Based Transfer Learning Assisted Framework for Skin Cancer Detection", IEEE Transactions, VOLUME 8, Page no: 147858 – 147871, 2020, **DOI:** 10.1109/ACCESS.2020.3014701