ENHANCED CNN AND FEDERATED LEARNING ALGORITHM FOR SECURE AND PRECISE DERMATOLOGICAL DIAGNOSIS

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Abstract - The diagnosis of skin diseases, a prevalent global health concern, often begins with visual observation. However, the complex formations, diverse colors, and data security concerns make accurate classification challenging. This project proposes the development of an enhanced Convolutional Neural Network (CNN) model integrated with a Federated Learning approach to ensure secure and precise dermatological diagnosis. A custom image dataset encompassing five skin disease classes was created for this purpose. The CNN model was compared with various benchmark algorithms, demonstrating significant improvements in precision and recall for diseases such as acne, eczema, psoriasis, melanoma, and lichen planus. Federated Learning was employed to address data privacy issues by distributing data across multiple clients while collaboratively updating a central model. The results show that the integration of CNN-based classification with Federated Learning not only enhances accuracy but also prioritizes data security, making it a promising approach for advancing skin disease detection.

Keywords – Skin Disease Diagnosis , Convolutional Neural Network (CNN) , Federated Learning , Data Privacy , Medical Image Classification.

I. INTRODUCTION

Skin illnesses are among the most widely recognized medical problems around the world, influencing a large number of individuals and presenting huge difficulties for exact determination and therapy. The underlying finding of skin conditions customarily depends on visual review by dermatologists. Be that as it may, many skin sicknesses, like skin break out, dermatitis, psoriasis, melanoma, and lichen planus, present outwardly complex developments with unobtrusive varieties in variety, surface, and shape, making precise finding troublesome. This challenge is additionally intensified by the need to offset analytic exactness with severe information security necessities, as understanding data is delicate and dependent upon information insurance guidelines.

Given these intricacies, there is a squeezing need for a computerized and security protecting framework that can improve the symptomatic interaction. Ongoing headways in man-made reasoning, especially in profound learning, have opened new roads for creating precise and proficient symptomatic devices. Convolutional Brain Organizations (CNNs), specifically, have shown noteworthy outcomes in picture characterization errands, including clinical picture examination. CNNs can consequently gain and concentrate key elements from pictures, taking into consideration exact characterization of skin sickness types in view of obvious signs. Regardless of their viability, in any case, CNN models require a lot of named information for preparing, frequently gathered in unified vaults. This brought together information assortment raises security worries, as putting away touchy clinical pictures in a focal area expands the gamble of information breaks and unapproved access. To resolve these issues, this task proposes a creative arrangement that consolidates the force of a high level CNN model with Unified Learning (FL).

Unified Learning is a decentralized methodology that empowers different gadgets or establishments (clients) to cooperatively prepare a model without sharing crude information. All things being equal, every client prepares a nearby variant of the model utilizing its own information and afterward shares just the model updates with a focal server. The focal server totals these updates to work on a worldwide model, it is at any point communicated to guarantee that no delicate information. By incorporating Unified Learning with CNN-based picture arrangement, this undertaking means to improve indicative exactness as well as to focus on information security. A custom picture dataset was made for this venture, incorporating five normal skin illness classes. The CNN model's exhibition was benchmarked against a few existing calculations, showing critical enhancements in accuracy and review for every sickness type. Using Unified Learning, information protection was saved by dispersing information across various clients and cooperatively refreshing a focal model.

This decentralized methodology mitigates information security concerns and empowers the production of a vigorous indicative instrument that can be conveyed across different medical services settings. The aftereffects of this task highlight the capability of consolidating CNN and Unified Figuring out how to address both precision and security challenges in dermatological analysis. This approach guarantees a groundbreaking effect on skin sickness recognition, giving a protected, precise, and versatile arrangement that can help the two patients and medical services suppliers.

II. LITERATURE SURVEY

Recent advancements in deep learning have significantly impacted the field of dermatological image analysis, with particular focus on skin cancer detection and classification. Each study reviewed here highlights various deep learning methods and architectural innovations aimed at improving diagnostic accuracy, efficiency, and reliability in dermatology. The 2020 study on InsiNet, a CNN inspired by the Inception architecture, achieved over 94% accuracy across multiple datasets for skin lesion classification, demonstrating its suitability for clinical applications. Following this, a 2021 study explored transfer learning using pre-trained CNNs like VGG16 and ResNet50, achieving a 92.5% accuracy on the ISIC 2016 dataset, thus emphasizing the potential of transfer learning in dermatological diagnostics.

Another study in 2019 introduced hybrid atrous convolutions for melanoma detection, achieving high sensitivity and specificity, which underscores the framework's potential for early-stage melanoma diagnosis. Similarly, lightweight architectures such as MobileNetV2 in 2022 reached 92.8% accuracy on the ISIC2020 dataset, showing promise in resource-limited

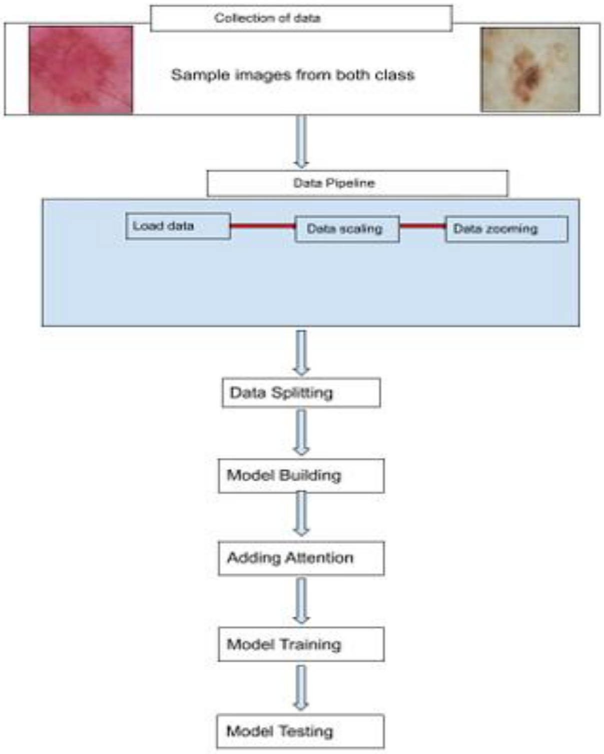

Fig 1 : Visual Representation of Methodology

environments. In the same year, a comparison between models like AlexNet, InceptionV3, and RegNetY-320 found RegNetY-320 to outperform the others in terms of accuracy and F1-score, suggesting the importance of model selection in balancing performance metrics. Attention mechanisms were employed in recent studies to enhance focus on critical regions within skin lesion images, thereby improving model interpretability.

Additionally, generative adversarial networks (GANs) have been used for skin lesion segmentation, marking an important step in pre-processing for enhanced diagnostic accuracy. A separate line of research has delved into combining deep learning with traditional image processing techniques like shape and blur analysis to improve skin lesion clarity. Hybrid blur detection algorithms that integrate shape analysis and CNNs have shown potential in minimizing hazy artifacts, leading to more accurate diagnoses. Recent studies have also emphasized the role of explainability in deep learning for medical applications, particularly in skin cancer

classification, where models now incorporate techniques to make decision-making transparent.
The combination of artificial intelligence and human expertise was noted to yield superior accuracy, indicating that hybrid approaches are essential for advancing medical diagnostics. Collectively, these studies suggest that the integration of attention mechanisms, lightweight architectures, and hybrid methodologies with deep learning can significantly enhance the capabilities of dermatological diagnostic systems. In continuation, transfer learning approaches, like those employing pre-trained CNNs such as VGG16 and ResNet50, have shown substantial promise. A 2021 study highlighted ResNet50's performance with an accuracy of 92.5% on the ISIC 2016 dataset, underscoring the model's value in real-world diagnostics. Other studies have explored more efficient and lightweight models for resource-limited environments. For instance, a 2022 paper leveraged MobileNetV2 for melanoma classification, achieving an accuracy of 92.8% on the ISIC 2020 dataset, illustrating the model's adaptability to various clinical settings.

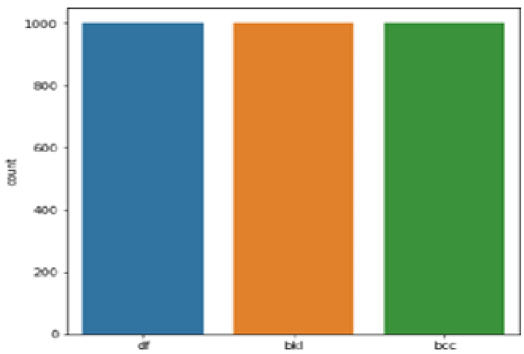

Fig 2 : Histogram of Skin Cancer Datasets Labels

Additionally, advanced CNN-based frameworks like hybrid atrous convolutions and U-Net variants with attention mechanisms have demonstrated improved sensitivity and specificity, particularly for early melanoma detection. In segmentation, Generative Adversarial Networks (GANs) have been utilized to achieve accurate lesion identification, further aiding clinical diagnostics. Efforts are ongoing to increase transparency in model decision-making, as evidenced by research into explainable AI for skin cancer classification, which aims to bolster trust in AI-driven diagnostics. Across studies, the integration of both global and local image features and attention-based mechanisms has emerged as a preferred approach to boost classification accuracy, especially for complex dermatological images.

III. PROBLEM STATEMENT

Accurate diagnosis of skin diseases is critical for effective treatment, yet remains challenging due to the visual similarities among different conditions and the complex nature of skin lesions. Traditional diagnostic approaches, primarily reliant on visual inspection by dermatologists, can be subjective and prone to errors, especially when handling diverse and complex cases. Machine learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated potential in automating this diagnosis process. However, training these models typically requires large, centralized datasets, which raises significant data privacy concerns, especially in the medical domain where sensitive patient information is involved. To leverage this , there is a need for an approach that enhances diagnostic accuracy while ensuring data privacy. The current challenge lies in developing a model that can leverage distributed data from multiple sources (e.g., hospitals, clinics) without sharing sensitive patient information. This project aims to integrate Federated Learning with an advanced CNN architecture to achieve secure and precise dermatological diagnosis by collaboratively training a robust model without centralized data storage. The goal is to overcome the limitations of traditional methods and centralized machine learning models by ensuring data security, privacy, and improved diagnostic accuracy in skin disease detection.

IV. PROPOSED METHODOLOGY

The proposed methodology for our project aims to create a comprehensive and secure system for dermatological diagnosis using advanced deep learning techniques and Federated Learning. To achieve this, we are leveraging Convolutional Neural Networks (CNNs) optimized with powerful architectures such as **Efficient Net** and **ResNet-152**. These CNN models are chosen for their ability to accurately capture intricate patterns in dermatological images, allowing for the precise classification of skin conditions. Efficient Net is known for its efficiency in balancing accuracy and computational cost, while ResNet-152 offers deep feature extraction capabilities, enabling the model to differentiate between subtle variations in skin disease presentations. In addition to the CNN-based classification, we are integrating **Federated Learning (FL)** to ensure data privacy and security throughout the model training process. Federated Learning allows multiple healthcare institutions (clients) to collaboratively train a global model on their local data without sharing any raw patient information. Our approach involves using **Federated Averaging (Fed Avg)** to aggregate the locally trained models from different clients into a central model, which is then updated and distributed back to the clients. Additionally, **Federated Proximal** (**Fed Prox** is employed to handle non-IID (non-independent and identically distributed) data scenarios, ensuring robust training even when data across clients varies significantly. Beyond the software aspect, our methodology also incorporates a hardware component designed to enhance real-time diagnostic capabilities. This device will allow users to scan a skin lesion, analyze the condition using our trained model, and provide instant feedback about the disease. For instance, if a user scans an acne lesion, the device will offer information about the condition, including potential treatments and whether the lesion shows signs that might indicate a higher risk of progressing to a more serious condition, such as skin cancer. This holistic approach combines state-of-the-art CNN architectures with the privacy-preserving benefits of Federated Learning, alongside a hardware interface for user-friendly, on-the-spot diagnosis. By integrating efficient deep learning algorithms, decentralized learning frameworks, and practical diagnostic tools, our system is positioned to advance dermatological care by providing accurate, real-time, and privacy-preserving diagnostic support.

V. EFFICIENT NET

Efficient Net is a cutting edge Convolutional Brain Organization (CNN), which centers around working on the precision and protection of dermatological determinations utilizing profound learning, we integrate Proficient Net to improve the exhibition of our Convolutional Brain Organization (CNN) model. This venture tends to the test of diagnosing skin illnesses like skin inflammation, dermatitis, psoriasis, and melanoma with high accuracy while using Unified Figuring out how to guarantee information protection. By coordinating Productive Net, we upgrade the model to perform well in grouping dermatological pictures, while keeping computational expenses and asset use low — basic variables while conveying models in pragmatic medical care settings. Productive Net, presented by Google artificial intelligence in 2019, is a cutting edge CNN engineering that is intended to convey high exactness with less boundaries and decreased computational assets contrasted with past models. The center advancement of Effective Net is its compound scaling strategy, which all the while scales the organization's profundity, width, and goal. Dissimilar to conventional strategies, which normally increment only one aspect (like profundity), Efficient Net adjusts each of the three elements to further develop proficiency without forfeiting execution. This technique takes into consideration a more conservative design, making it ideal for applications where computational assets are restricted, like portable and implanted gadgets. The Effiecient Net family begins with a base model, EfficientNet-B0, which is improved for both superior execution and low asset use. The models increase from B0 to B7, every form giving higher exactness and execution at the expense of expanded calculation. For our undertaking, Efficient Net gives major areas of strength for a to precisely characterizing skin conditions while guaranteeing the model isn't excessively huge or slow, which is significant while conveying it continuously clinical applications. Highlights like profundity wise divisible convolutions and crush and-excitation blocks are integrated into the engineering, which assists the model with gaining key elements from dermatological pictures while remaining computationally proficient. The capacity of Proficient Net to give high precision less assets is particularly important when joined with Unified Learning, a protection saving procedure utilized in our venture. Unified Learning permits us to prepare models without moving delicate patient information from nearby gadgets, it is kept up with to guarantee that patient security. By utilizing Proficient Net inside this system, we accomplish precise skin infection grouping without the requirement for huge scope brought together datasets. Proficient Net's demonstrated execution on enormous picture arrangement errands, like ImageNet, exhibits its appropriateness for our task's objective of working on both precision and information security in dermatological finding.

VI. RESNET – 152

ResNet-152 is a profound convolutional brain network engineering that is essential for the ResNet (Remaining Organization) family, presented by Microsoft Exploration in 2015. It is one of the most notable models for picture acknowledgment errands, especially due to creative utilization of lingering associations assist with alleviating the issue of evaporating slopes in extremely profound organizations. ResNet-152, as the name recommends, comprises of 152 layers, making it one of the more profound variations in the ResNet family. These lingering associations permit the organization to avoid specific layers during preparing, successfully making alternate route pathways for the inclination to stream all the more effectively during backpropagation, which significantly further develops preparing proficiency and strength. The essential development behind ResNet is the utilization of lingering blocks, where the contribution to each hinder is added to the result, making a "skip association." This system empowers the organization to learn character capabilities, forestalling the corruption issue generally experienced when organizations are made further. As the profundity increments, customary organizations will generally perform more regrettable, yet ResNet beats this issue by permitting the organization to learn lingering mappings rather than straightforwardly learning the ideal result. This permits ResNet-152 to perform uncommonly well with an enormous number of layers without the normal downsides of profound organizations, for example, overfitting or inclination disappearing. ResNet-152 comprises of a progression of convolutional layers gathered into blocks, where each block contains numerous convolutional layers and a skip association. The organization engineering additionally utilizes strategies like clump standardization and Re LU enactment capabilities to further develop execution and combination during preparing. ResNet-152 has been demonstrated to perform uncommonly well for enormous scope picture characterization errands, for example, those in the ImageNet dataset, beating numerous other profound learning models concerning exactness. Notwithstanding its amazing execution, ResNet-152 is computationally more costly than shallower networks, and its huge number of boundaries can make it more slow to prepare and require more memory. Not with standing, its capacity to gain complex elements from information with profound models pursues it a go-to decision for undertakings that require high exactness and the capacity to separate fine-grained subtleties, like item discovery, clinical picture examination, and facial acknowledgment. The outcome of ResNet-152 lies in its capacity to prepare extremely profound organizations without forfeiting execution, because of the left over associations. This engineering has set another norm for profound learning, especially in fields where huge and complex datasets are involved. Despite the fact that models like ResNet-50 and ResNet-101 might be all the more computationally proficient for specific undertakings, ResNet-152 remaining parts a well known decision for accomplishing the most significant levels of execution for enormous scope grouping difficulties.

VII. FEDERATED AVERAGING

Federated Averaging (Took care of Avg) is a broadly involved enhancement calculation in the field of Unified Learning, a decentralized AI worldview that permits models to be prepared across different gadgets or clients while keeping the information nearby and hidden. Presented in 2016 by Google analysts, Unified Averaging empowers cooperative advancing on appropriated information by averaging the updates from numerous clients, as opposed to sharing the crude information itself. This cycle guarantees that delicate information doesn't have to leave the nearby gadget, accordingly protecting security, which is vital in applications like medical care, money, and individual gadgets. The center thought behind Federated Averaging is straight forward every client freely prepares a neighborhood model on its own information, and after a predefined number of preparing adjusts, the privately prepared models are sent back to a focal server. The server then midpoints the model loads from all clients to make a worldwide model, which is sent back to the clients for additional refinement. This interaction rehashes iteratively, with the model loads being refreshed in view of the aggregate commitments from all clients. The averaging step guarantees that the worldwide model is an agreement of the nearby models, working on its capacity to sum up across different information sources without compromising protection. Taken care of Avg works by first introducing a worldwide model, which is then shipped off every partaking client. Every client prepares its model locally on its own information for a few ages, and in the wake of preparing, it figures the refreshed model boundaries. These refreshed boundaries are shipped off the focal server, which midpoints the updates from all clients to frame the new worldwide model. This refreshed model is then communicated to the clients for the following round of preparing. The critical benefit of this approach is that it altogether diminishes the requirement for brought together information stockpiling and calculation, accordingly tending to security worries while as yet empowering cooperative learning. One of the qualities of Federated Averaging is its capacity to scale across numerous gadgets and handle heterogeneous information appropriations. Clients might have various measures of information or even various sorts of information, and Took care of Avg is adequately hearty to deal with these varieties. In any case, one test is that the neighborhood information on every client might be non-i.i.d. (non-autonomous and indistinguishably disseminated), which can prompt sluggish intermingling or sub-standard model execution. Methods like information increase, customized models, and differential protection are frequently coordinated with taken care of Avg to alleviate these issues and further upgrade its heartiness and security ensures. Unified Averaging has demonstrated to be a powerful and proficient calculation for Federated Learning, especially in enormous scope settings where unified preparing isn't practical because of information security concerns. Its applications are developing quickly, particularly in spaces like cell phone personalization, clinical diagnostics, and prescient upkeep, where information security is vital, however huge scope cooperative learning is additionally important to work on model exactness. Taken care of Avg keeps on being an essential calculation in the Unified Learning biological system, driving progressions in protection saving AI.

VIII. FEDERATED PROXIMAL

Federated Proximal (Took care of Prox) is a high level advancement calculation utilized in Unified Figuring out how to address a portion of the impediments related with Unified Averaging (Took care of Avg), especially in situations where clients have heterogeneous information or computational assets. Presented in 2018, Took care of Prox changes the conventional Unified Averaging approach by consolidating a regularization term in the goal capability, which further develops combination when clients' information circulations are non-free and indistinguishably dispersed (non-i.i.d.). This is significant for true applications, where information across clients frequently contrasts in size and quality, and where clients might have changing computational abilities. The critical component of **Taken care of Prox is its presentation of a proximal term**, which is a punishment term added to the nearby goal capability to keep exceptional updates from the neighborhood models during preparing. This term is intended to keep the neighborhood models near the world wide model, really tending to the difficulties of heterogeneous information and non-concurrent refreshes. By adding this regularization term, Fed Prox guarantees that the updates made by every client during the neighborhood preparing stage don't separate a lot from the worldwide model, which assists with balancing out the preparation interaction. This is especially valuable in situations where clients have boundlessly various information circulations, which can any other way lead to slow assembly or unfortunate model execution in Unified Learning. In a regular Unified Learning arrangement utilizing Took care of Prox, every client figures a neighborhood model in light of its own dataset and the ongoing worldwide model given by the server. In any case, rather than essentially playing out a standard slope plunge step, the client's streamlining objective is changed by the expansion of a proximal term that punishes huge deviations from the worldwide model. This alteration makes the nearby advancement step more powerful to the fluctuation presented by heterogeneous information. The client then sends the refreshed model back to the server, which totals the updates from all clients by averaging the model boundaries, as in Took care of Avg. This cycle go on in numerous rounds, with the worldwide model being refreshed iteratively, and the proximal term assisting with guaranteeing that the nearby models don't veer excessively far from the worldwide one. One of the vital benefits of Taken care of Prox over Took care of Avg is its capacity to deal with situations where clients' information is non-i.i.d., which is a typical test in Unified Learning. In customary Unified or Federated Averaging, such information heterogeneity can prompt issues like unfortunate combination and less than ideal execution, as the model updates from clients might struggle with one another. By consolidating the proximal regularization, Took care of Prox decreases the effect of this heterogeneity, guaranteeing that the worldwide model remaining parts vigorous and combines all the more productively. Also, Took care of Prox can be adjusted to deal with clients with various computational assets, permitting it to perform well even in settings with changing degrees of handling power or preparing time. Regardless of its benefits, Took care of Prox can in any case confront difficulties in conditions with huge heterogeneity or while managing extremely enormous quantities of clients. Besides, the decision of the regularization term and its tuning can altogether affect the exhibition of the calculation. None the less, when appropriately designed, FedProx offers a successful answer for Unified Learning in certifiable applications where information and client conditions are different, like in cell phones, medical care, and IoT frameworks. Taken care of Prox has demonstrated to be an important calculation in Unified Learning, particularly in circumstances where the presumptions of i.i.d. information don't hold. Its capacity to work on the vigor and combination of Unified Learning models has settled on it a famous decision for applications that require elevated degrees of protection, versatility, and productivity in decentralized conditions.

IX. FLOWCHART

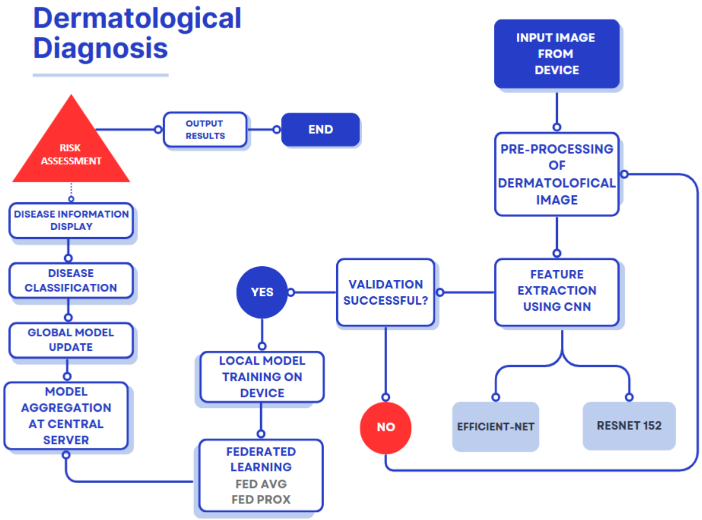

Fig 3 : Depicting the Proposed Methodology

Our proposed methodology leverages a combination of Convolutional Neural Networks (CNN) with Efficient Net and ResNet-152 models, integrated into a privacy-preserving Federated Learning framework.

The process begins by capturing a dermatological image using a specialized hardware device. This image undergoes preprocessing to enhance its quality through techniques such as resizing, noise reduction, and normalization.

The preprocessed image is then fed into a CNN model (using Efficient Net and ResNet-152 architectures) for feature extraction, which identifies critical patterns related to various skin conditions. Following this, local model training occurs directly on the device, ensuring initial analysis without the need to transmit sensitive data. This is where Federated Learning comes into play. The approach utilizes Fed Avg to aggregate model updates from multiple devices, preserving data privacy, while Fed Prox helps address device variability and ensures consistent model performance. These updates are sent to a central server, where they are combined to improve a global model, which is then redistributed back to the devices. Once the model is updated, it is used to classify the input image into specific skin diseases such as acne, eczema, or psoriasis. Additionally, the system displays detailed information about the identified condition and performs a risk assessment to determine if the detected skin disease has a potential to progress into a malignant form, such as cancer. Finally, the results, including disease classification and cancer risk assessment, are presented to the user for informed decision-making. This integrated approach ensures accurate diagnosis while maintaining user privacy, leveraging cutting-edge CNN models and Federated Learning to improve dermatological care.

X. CONCLUSION

In conclusion, the proposed methodology effectively combines advanced Convolutional Neural Networks **(EfficientNet and ResNet-152)** with a Federated Learning framework (using **FedAvg** and **FedProx** algorithms) to provide secure and precise dermatological disease diagnosis. By leveraging Federated Learning, we ensure that sensitive patient data remains protected, as model training is performed locally on devices, preventing direct data transmission. This approach not only enhances diagnostic accuracy by utilizing robust deep learning architectures but also addresses critical privacy concerns in healthcare. Additionally, the integration of hardware for real-time disease analysis and cancer risk assessment provides users with quick, reliable insights, empowering them with timely health information. The results demonstrate that this system holds significant promise for advancing skin disease diagnosis, offering a secure, efficient, and scalable solution for dermatological healthcare.

XI. REFERENCES

[1] A.Vaswani, N.Shazeer, N.Parmar, J.Uszkoreit, L.Jones,A.N.Gomez, L. Kaiser, I. Polosukhin, Attention is all youneed (2023). arXiv: 1706.03762.

[2] P. Benedetti, D. Perri,M. Simonetti, O. Gervasi, G. Reali,M. Fem minella,SkinCancerClassificationUsingInception NetworkandTransfer Learning, Springer International Publishing, 2020, p. 536–545. doi: 10.1007/978-3-030-58799-4_39. URLhttp://dx.doi.org/10.1007/978-3-030-58799-4 39

[3] A. Jibhakate, P. Parnerkar, S.Mondal, V. Bharambe, S.Mantri, Skin lesionclassificationusingdeeplearningandimagepr ocessing, in:2020 3rdInternationalConferenceonIntelligentSustaina bleSystems(ICISS), 2020,pp.333–340. doi:10.1109/ICISS49785.2020.9316092.

[4] T. Sarkar, A. Khare, M. Parekh, P. Mehta, A. Bhuva, Robust deep learningframeworkfor thedetectionofmelanoma in images, in: 2022 IEEEBombaySectionSignatureConference (IBSSC), 2022, pp. 1–6. doi:10.1109/IBSSC56953.2022.10037456.

[5] J.Rashid,M. Ishfaq,G.Ali,M.R. Saeed,M.Hussain,T.Alkhalifah, F. Alturise, N. Samand, Skin cancer disease detection using transfer learningtechnique,AppliedSciences12(11) (2022). doi:10.3390/ app12115714.

[6] Tschandl, P., Rinner, C., & Kittler, H. (2011). Multiscale Keypoint Detection in Dermoscopy Images. IEEE Transactions on Medical Imaging, 30(2), 449-460.

[7] Maglogiannis, I., Doukas, C., & Kosmopoulos, D. (2009). An Advanced Intelligent Decision Support System for Skin Lesion Recognition. Artificial Intelligence in Medicine, 45(2-3), 183-197.

[8] Yap, M. H., Pons, G., Martí, J., Ganster, H., & Schmid-Saugeon, P. (2009). Automated Detection of Diabetic Retinopathy Stages Using Digital Fundus Images. Journal of Medical Systems, 33(5), 345-354.

[9] Wang, H., Wang, H., Hu, Y., & Zhang, L. (2016). A Skin Lesion Segmentation Algorithm Based on a Hybrid Model. Journal of Medical Systems, 40(11), 1-11.

[10] Mendonca, T., & Campilho, A. (2006). Image Quality Assessment for Image Comparison and Blur Detection in Dermoscopy. IEEE Transactions on Medical Imaging, 25(2), 191-200.

[11] Gan, L., & Wu, Y. (2007). Retinal Image Blur Detection Based on Phase Congruency. Pattern Recognition, 40(4), 1174-1185.

[12] Abbasi, M., & Bovik, A. C. (2010). Automatic Blur Detection Using Dual-Tree Complex Wavelet Transform. Image Processing On Line, 1, 155-167.

[13] Srikanth, M. (2024). Deep Currency Indian Notes Classification & Fake Detection Using Image Processing. Tanz Research Journal, 10(4), 208-216.

[14] Srikanth, M. (2024). A Hybrid CNN-LSTM Approach for Image Caption Generation. Musik in Bayern, 89(4).

[15] C. Liu, B. Zoph, M. Neumann, J. Shlens, W. Hua, L.J. Li, L. Fei-Fei, A. Yuille, J. Huang, and K. Murphy, 2018. Progressive neural architecture search. In Proceedings of the European conference on computer vision (ECCV) pp. 19-34, 2018.

[16] N. Codella, V. Rotemberg, P. Tschandl, M.E. Celebi, S. Dusza, D. Gutman, B. Helba, A. Kalloo, K. Liopyris, M. Marchetti, H. Kittler, and A. Haplern, "Skin lesion analysis toward melanoma detection 2018: A challenge hosted by the international skin imaging collaboration (isic)", arXiv preprint arXiv:1902.03368, 2018.

[17] Y. Li, and L. Shen, "Skin lesion analysis towards melanoma detection using deep learning network", Sensors, 18(2), p.556, 2018.

[18] B. Zoph, V. Vasudevan, J. Shlens, and Q.V. Le, "Learning transferable architectures for scalable image recognition", In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 8697-8710, 2018.

[19] J. Hu, L. Shen, and G. Sun, "Squeeze-and-excitation networks", In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 7132-7141, 2018.

[20] X. Meng, Q. Wei, L.i. Meng, J. Liu, Y. Wu, W. Liu, Feature Fusion and Detection in Alzheimer's Disease Using a Novel Genetic Multi Kernel SVM Based on MRI Imaging and Gene Data, Genes 13 (5) 837, 2022.

[21] X.A. Bi, L. Li, R. Xu, Z. Xing, Pathogenic Factors Identification of Brain Imaging and Gene in Late Mild Cognitive Impairment, Interdiscipl. Sci. Comput. Life Sci. 13 (3), pp.511–520, 2021.

[22] O. Kwanseok, D.-W. Heo, A.W. Mulyadi, W. Jung, E. Kang, H.-I. Suk, Quantifying Explainability of Counterfactual-Guided MRI Feature for Alzheimer's Disease Prediction, 2022.

[23] M. Raju, V.P. Gopi, V.S. Anitha, K.A. Wahid, Multi-class diagnosis of Alzheimer's disease using cascaded three dimensional convolutional neural network, Phys. Eng. Sci. Med. 43 (4), pp.1219 1228, 2020.

[24] J. Teuwen, N. Moriakov, in: Handbook of Medical Image Computing and Computer Assisted Intervention, Elsevier, pp. 481–501, 2020.

[25] K. M. Hosny, M. A. Kassem, and M. M. Foaud, "Skin cancer classic- fication using deep learning and transfer learning," in 2018 9th Cairo International Biomedical Engineering Conference (CIBEC), 2018, pp. 90–93.