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Deep Learning based Model for Detection of Vitiligo Skin Disease using Pre-trained Inception V3

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Abstract
Skin diseases are commonly identified problems all over the world. There are various kinds of skin diseases, such as skin cancer, vulgaris, ichthyosis, and eczema. Vitiligo is one of the skin diseases that can occur in any area of the body, including the inner part of the mouth. This type of skin can have immense negative impacts on the human body, involving memory issues, hypertension, and mental health problems. Conventionally, dermatologists use biopsy, blood tests, and patch testing to identify the presence of skin diseases and provide medications to patients. However, these treatments don't always provide results due to the transformation of a macule into a patch. Various machine learning (ML) and deep learning (DL) models have been developed for the early identification of macules to avoid delays in treatments. This work has implemented a DL-based model for predicting and classifying vitiligo skin disease in healthy skin. The features from the images have been extracted using a pre-trained Inception V3 model and substituted for each classifier, namely, naive Bayes, convolutional neural network (CNN), random forest, and decision tree. The results have been determined as accuracy, recall, precision, area under the curve (AUC), and F1-score for Inception V3 with naive Bayes as 99.5%, 0.995, 0.995, 0.997, and 0.995, respectively. The Inception V3 with CNN has achieved 99.8% accuracy, 0.998 recall, 0.998 precision, 1.00 AUC, and 0.998 F1-score. Further, Inception V3 with random forest shows 99.9% accuracy, 0.999 recall, 0.999 precision, 1.00 AUC, and 0.999 F1-score values whereas, Inception V3 with decision tree classifier shows an accuracy value of 97.8%, 0.978 recall, 0.977 precision, 0.969 AUC, and 0.977 F1-score. Results exhibit that Inception V3 with a random forest classifier outperforms in terms of accuracy, recall, precision, and F1-score, whereas for the AUC metric, Inception V3 with a random forest and Inception V3 with CNN have shown the same outcomes of 1.00.

Keywords- InceptionV3, Convolutional neural networks, Vitiligo, Naive Bayes, Random forest, Decision tree.

1. Introduction

Vitiligo is a skin disease that can affect humans in such a way that the patient loses their skin colour and acquires unpigmented and patchy skin (Guo et al., 2022). As per the previous studies presented (Guo et al., 2022), vitiligo is a skin disease that affects 0.2% to 1.8% of people all over the world. The benign nature of vitiligo can be common, but with its increase in the visible areas of the body such as hands, face, mouth, etc., it becomes a disease that needs to be treated to avoid anxiety, low self-confidence, and depression issues (Ma et al., 2023). Vitiligo creates a lighter skin tone than the original skin colour. The human skin that loses colour and has an area affected by less than 1cm is called a macule; if it is larger than 1cm, it is called a patch. Vitiligo is a catastrophic disease that can directly impact the life span if it goes untreated and increases (Zhang et al., 2021). The progression of vitiligo can be slow or very fast. The disease occurs when there is an instant slowdown in the cells responsible for the pigmentation in the skin. This skin disease can occur in any part of the body, but people with a dark complexion are the main focus due to the instant and clear visibility of the disease (Leachman et al., 2020; Zhang et al., 2021). Vitiligo is an autoimmune ailment that is also known as leucoderma. There are various therapies for vitiligo, such as systemic therapy, phototherapy, and depigmentation therapy, but their results are not always satisfactory, and these treatments are also very costly and time-consuming. Additionally, repigmentation is also a solution for vitiligo skin disease; however, it is also a time-consuming process that takes almost 3–6 months, or sometimes more than that, for the proper creation of the pigmentation in the skin, and sometimes it is not effective and may lead to many side effects. The vitiligo gets too severe and affects the hair as well as the inner mouth areas. The treatments that have been identified as the best methods for removing vitiligo can be implemented only on the outer mouth areas. With time, vitiligo disease gets worse, and only the new patches can be treated, while the older patches can't be treated with the therapies. This disease can sometimes occur due to hereditary factors or be triggered by stress, skin trauma, severe sunburn, or high contact with chemicals. This skin type can cause hearing loss, weakened eyesight, and psychological or social distress. With the occurrence of such diseases, various patients feel mortification and indignity, which may lead to stress and mental health issues. The increased lunacy of the human brain can cause a massive loss of memory and intelligence. The macule of vitiligo can be treated very quickly if it is identified, while the patches take time to get treatment with therapies. This skin disease requires expert advice for treatments if it is diagnosed (Rushdi & Rushdi, 2018). There are various skin problems that look similar in the initial stages, including the similarity between macules and freckles; it becomes difficult and time-consuming to classify them. Figure 1 shows the vitiligo skin disease.

Figure 1. Vitiligo (Neri et al., 2020).

The stage identification of the skin disease is also a challenging task, necessitating identifying the difference between freckled skin and a life-threatening vitiligo disease (Mudunuru & Skrzypek, 2020). Various studies have been performed to classify skin diseases using ML and DL methods. The ML and DL models provide extensive applications in various domains for classification (Pal et al., 2022; Sharma et al., 2022a; Singh & Ramkumar, 2022). ML models help in identifying the existence of the disease in the text data, while DL models are applicable to classify the images with accurate feature extraction (Sharma et al., 2022b). Additionally, these models are responsible for the early prediction of various detrimental diseases and lead to decreased mortality along with economic growth due to the reduction in contamination by skin diseases. In the proposed work, the pre-trained feature extractor Inception V3 with four different classifiers, naive Bayes, random forest, decision tree, and CNN, has been used for the classification of vitiligo and healthy skin. This work can support healthcare systems with accurate feature extraction in the images and may result in better skin disease classification.

The contribution of the proposed work is mentioned below:
- The proposed work performs an early prediction of Vitiligo skin disease using deep learning.
- The model performs feature extraction using the pre-trained deep learning model Inception V3, and classification is done using classifiers: neural networks, naïve Bayes, decision tree, and random forest.
- The performance of the proposed model for Vitiligo skin disease has been compared with Inception V3 with Naïve Bayes, Inception V3 with a decision tree, Inception V3 with a random forest, Inception V3 with a neural network, and existing research. The performance results exhibit that the proposed model, Inception V3, with random forest outperforms other models.

Apart from the introduction, the article includes five additional sections. Section 2 describes the existing work with details of the technique, dataset, and performance results, and Section 3 introduces a detailed description of the dataset and proposed methodology. The results of the proposed model have been discussed in Section 4. Lastly, the conclusion has been presented in Section 5.

2. Literature Review on Machine Learning and Deep Learning Models for Vitiligo Skin Diagnosis

In Guo et al. (2022), authors have implemented an artificial intelligence model for morphometrically and colourimetrically measuring the presence of vitiligo disease. For its implementation, two different datasets containing 2,720 and 1,262 images have been utilized. These images have been segmented using deep convolutional neural networks (DCNNs), UNet, and UNet++, along with pyramid scene parsing network (PSPNet) models. Furthermore, the model with the highest performance has been integrated to form a single model to predict disease detection performance. The classification has been done using the ImageNet model, which has shown an accuracy result of 92.91%. In Saini & Singh (2022), the authors have used two classifiers, namely, the K-nearest neighbour (KNN) and the voting classifier, for predicting the existence of vitiligo skin disease. The dataset has been divided into two parts, i.e., train and test. The training images were pre-processed, and then a grey-level co-occurrence matrix (GLCM) model was applied to identify the essential features and store them in the database. Further, the test images have also been pre-processed, and the features were identified using the KNN model. Lastly, both the features of the test and train datasets have been implemented with a voting classifier, and results have been mentioned in terms of accuracy as 75%.

In Bashar & Alsaid Suliman (2022), the implementation of four different DL techniques, namely, VGG19, InceptionResNetV2, and ResNext101, along with Inception V3, has been done for classifying healthy and vitiligo skin. The results of the study were identified in AUC and ROC. The dataset used in the research contained 1341 images, and a k-fold cross-validation was applied. In the results, it has been concluded that the Inception V3 shows the best performance with an AUC value of 0.9111, while the InceptionResNetV2 has resulted in the lowest AUC outcome of 0.8560. In Ahammed et al. (2022), the authors have implemented three ML models, namely support vector machine (SVM), KNN, and decision tree, for identifying benign keratosis, actinic keratosis, dermatofibroma, vascular lesions, and many others. For the successful implementation, two datasets, i.e., HAM10000 and ISIC 2019, were used, and their results were compared with the existing models to validate the proposed work.

In Wang et al. (2021), the authors combined greedy articulation point removal (APR) and a random forest model to identify the necessary therapeutic targets for vitiligo skin disease. The authors concluded with an achieved AUC of 0.926. In Agrawal & Aurelia (2021), the authors have built a transfer learning model for classifying three different diseases, i.e., vitiligo, melanoma, and vascular tumors. Inception V3 has been implemented as the base model for skin disease classification. The steps involved in the networks are pre-training and fine-tuning the model.

In Awasekar (2021), the authors presented an ML model for classifying vitiligo and ringworm skin. This study utilized a dataset collected from various patients. Various techniques were applied to the images, such as pixel enhancements, segmentations, feature extractions, and the final analysis, for better outcomes. In Thanka et al. (2020), authors have implemented the DCNN model for classifying nine skin diseases, including vitiligo, eczema, melanoma, and many others. The dataset contained 1800 images by combining the data for all the diseases. Table 1. show the details of the techniques, datasets, and performance outcomes of the existing work.

Table 1. Comparison of the state-of-the-art in terms of models, datasets, and performance outcomes.

References	Technique	Dataset	Performance
Guo et al. (2022)	DCNN, UNet, UNet++, and PSPNet	Chinese patients' datasets Dataset I: 2720 images Dataset II: 1262 images	Accuracy: 92.91%
Saini & Singh (2022)	KNN, GLCM, K-means, and voting classifier	Vitiligo dataset	Accuracy: 75%
Bashar & Alsaid Suliman (2022)	VGG19, InceptionResNetV2, ResNext101, and Inception V3	The dataset was collected from DermNet, Kaggle, AtlasDerm, DermIS, and DanDerm, etc.	InceptionResNetV2 AUC: 0.856, Inception V3 AUC: 0.911
Ahammed et al. (2022)	SVM, KNN, and decision tree	HAM10000 and ISIC 2019	—
Wang et al. (2021)	Combined APR and random forest model	GSE65127, GSE75819, and GSE53146	AUC: 0.926
Agrawal & Aurelia (2021)	Inception V3	Vascular tumour, melanoma, and vitiligo dataset collected from Kaggle	Accuracy: 97.63%
Awasekar (2021)	ML model	Kaggle and DERMATOLOGY ATLAS dataset	—
Thanka et al. (2020)	DCNN	Dermnet dataset	Accuracy: 96%

3. Material and Methods

This section elaborates on the dataset and methodology used to implement the proposed model for vitiligo skin disease. In the proposed work, feature extraction has been done using pre-trained Inception V3, while classification has been performed using random forest, naive Bayes, decision tree, and CNN models.

A. Dataset

The dataset used for the implementation has been collected from Kaggle (Zienab_esam, 2022), which contains 1202 images, including healthy and vitiligo skin diseases. Furthermore, this dataset is divided into train and test directories; the train directory has 961 images, while the test directory has 241 images.

B. Proposed Methodology for Vitiligo Skin Disease Prediction

The proposed methodology includes feature extraction and classification, in which feature extraction has been performed by Inception V3, while random forest, naive Bayes, decision tree, and CNN models have been used for classification. There are two output classes in the results, i.e., healthy skin and vitiligo skin disease. Vitiligo skin occurs when there is an instant drop in the pigmentation cells, leading to an even skin tone. This disease can cause an increase in psychological stress along with weakened vision. The proposed methodology has been divided into four major steps, which include data splitting, feature extraction, and applying ML and DL models along with prediction. The proposed work utilizes the orange 3.32.0 simulator for its implementation. At the initial stage, the complete dataset was used, and a split of 80:20 was done to train and test the ML and DL models. Initially, the complete dataset was in a single folder containing sub-folders of healthy and vitiligo skin disease images. In the next step, the pre-trained Inception V3 model was applied to the images to extract relevant features. Inception V3 is a well-known model for object detection and feature extraction developed by Google in 2014. There are various variants of Inception, such as Inception V1, Inception V2, and Inception V3. This model has less computation efficiency, replaces the larger convolutions with smaller ones, and takes less time to process (Kurama, 2020). Due to advancements in Inception V3, it has been used in the proposed work to extract the necessary features from the images.

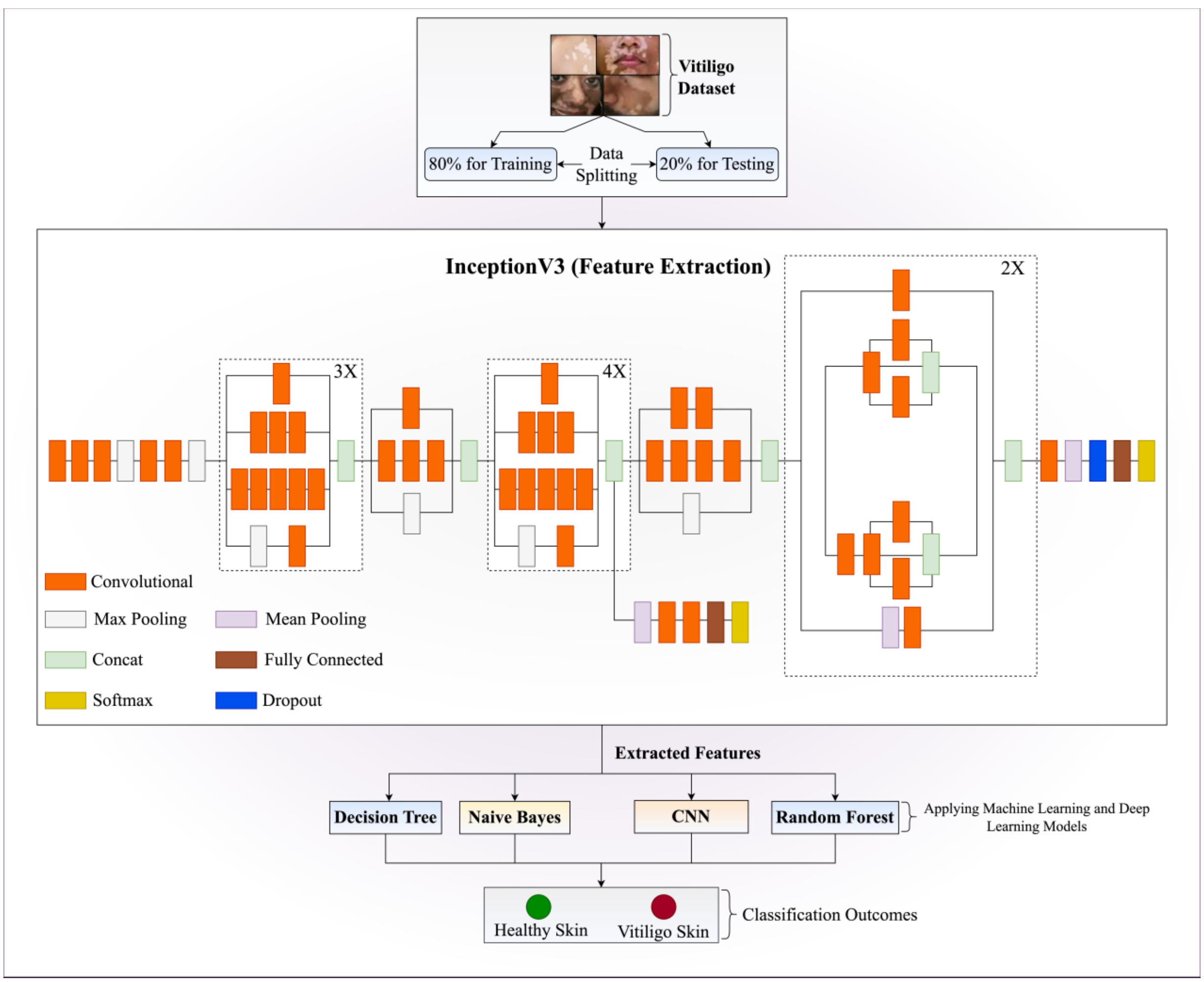

Figure 2. Proposed workflow of methodology for the vitiligo skin disease prediction.

Furthermore, naive Bayes, decision tree, random forest, and CNN classifiers have been used for classification. CNN is a well-known model for disease detection, while naive Bayes, random forest, and decision tree have been used to identify how ML classifiers perform when fed with an image dataset (Sonawane et al., 2023). Finally, the results of these models have been analyzed in terms of performance metrics, namely accuracy, recall, F1-score, precision, and AUC, along with ROC. The methodology used in the proposed work is shown in Figure 2. The mechanism of each classification model used for prediction works differently. The proposed decision tree classification model for the prediction of vitiligo and healthy skin has been shown in Figure 3, where the number of instances in the leaf node is 2 and the maximum tree depth has been kept at 100.

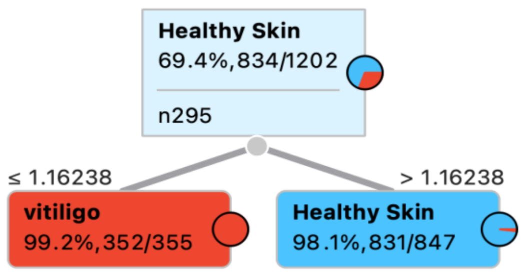

Figure 3. Proposed decision tree for the prediction of vitiligo and healthy skin.

Figure 4 depicts the proposed decision tree classifier when the target class has been kept as vitiligo skin.

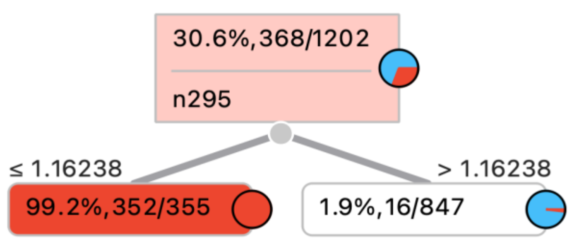

Figure 4. Proposed decision tree for the prediction of vitiligo skin.

Figure 5 shows the proposed decision tree classifier for healthy skin as the target class.

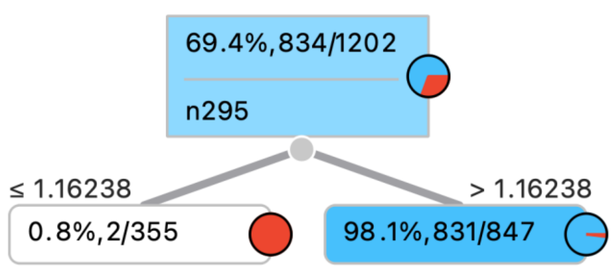

Figure 5. Proposed decision tree classifier for the prediction of healthy skin.

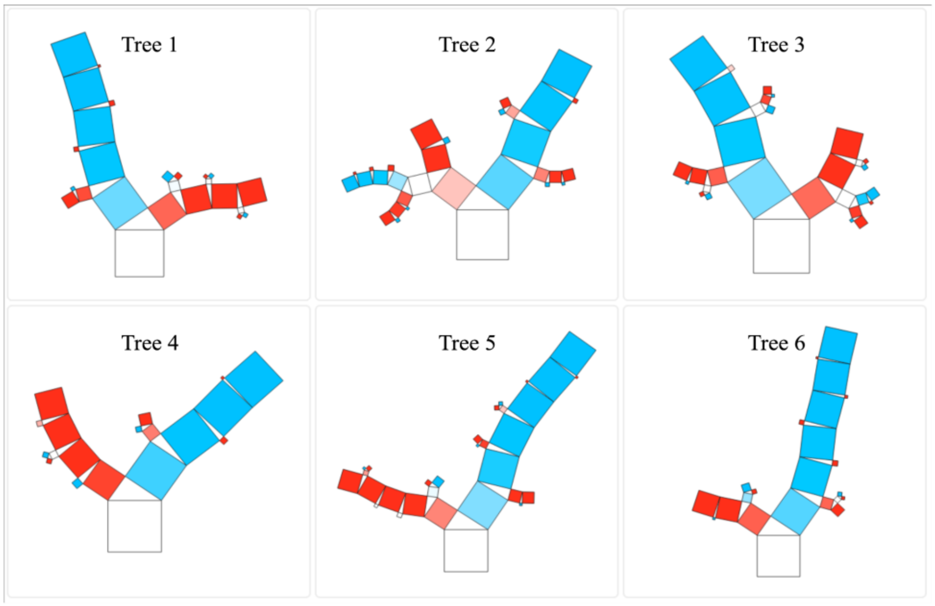

Figure 6. Representation of decision tree in the proposed random forest classification model for the prediction of vitiligo and healthy skin.

Figure 6 shows the learned decision tree from the proposed random forest classifier, where the number of trees for the construction model was 6. Each tree has shown different outcomes for the prediction of vitiligo and healthy skin. Tree 4 has shown the best classification performance due to the least depth along with very less attribute split in the tree branches.

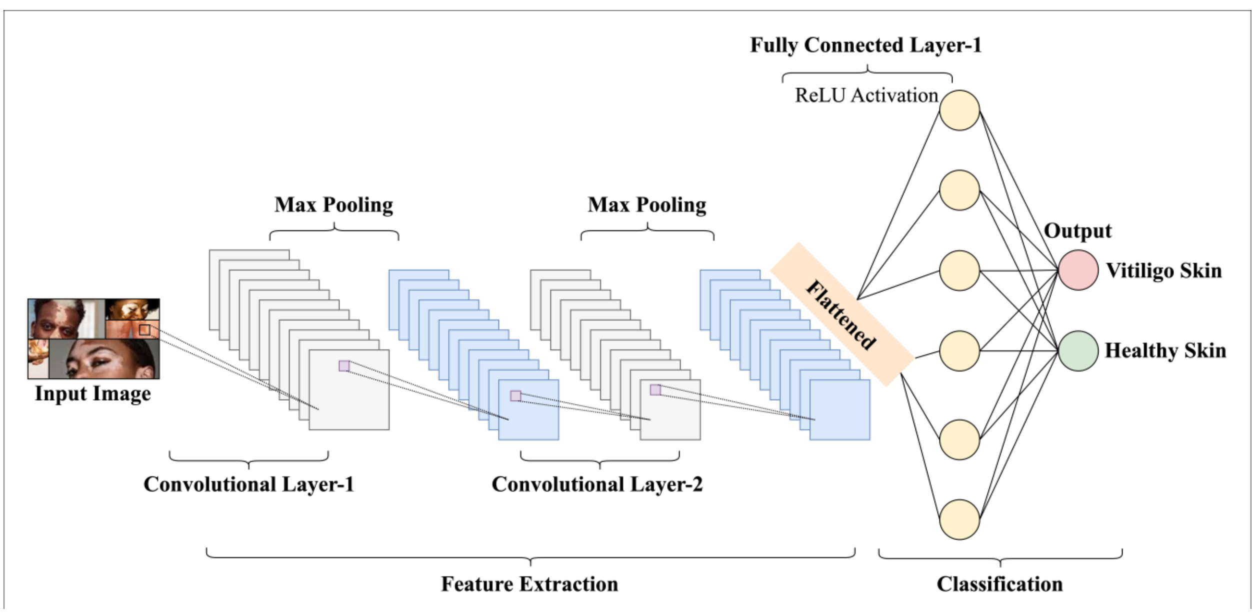

Figure 7. Representation of the proposed convolutional neural network classifier for the prediction of vitiligo and healthy skin.

Figure 7 represents the architecture of the proposed CNN classifier for the early prediction of vitiligo and healthy skin. This model contains convolutional layers for feature extraction and pooling layers for dimensionality reduction. The flattening layer is responsible for converting the output of an N-dimensional array to a single-dimensional array. Furthermore, the fully connected layer combines each neuron from the flattening layer to predict the output in the output layer.

In practice, the proposed method can be used in healthcare applications to slow down the progression of vitiligo disease by performing early prediction of the disease, allowing for quick medical intervention. Further, it can also help in effective treatment and successful re-pigmentation results when detected at early stages. The proposed model for automatically detecting vitiligo will be a useful resource for dermatologists in their clinical work. This method has the potential to significantly reduce the time needed for diagnosis and treatment planning by enabling effective analysis of a large number of skin images, increasing overall productivity and prediction performance. The proposed skin detection model is also applicable to differentiating between freckles and vitiligo skin, which can avoid disease interpretation and misdiagnosis.

4. Results and Discussion

This section describes the results obtained using the Inception V3 feature extractor with various classifiers, including random forest, CNN, decision tree, and naive Bayes, to classify healthy and vitiligo skin diseases. The results exhibit that Inception V3 with naive Bayes shows the performance outcomes as 99.5% accuracy, 0.995 recall, 0.995 precision, 0.997 AUC, and 0.995 F1-score. Inception V3 with random forest shows 99.9% accuracy, 0.999 recall, 0.999 precision, 1.00 AUC, and 0.999 F1-score. Further, Inception V3 with the decision tree shows 97.8% accuracy, 0.978 recall, 0.977 precision, 0.969 AUC, and 0.977 F1-score, while Inception V3 with CNN shows 99.8% accuracy, 0.998 recall, 0.998 precision, 1.00 AUC, and 0.998 F1-score. Additionally, the results of each model have been compared and illustrated for each performance metric.

A. The Comparative Analogy of Proposed Models

Figure 8 shows an accuracy comparison of the proposed work. This comparison identifies that Inception V3 with random forest outperforms all other models by exhibiting 99.90% accuracy. Nevertheless, the overall accuracy of Inception V3 with the CNN classifier is 99.80, which is also very good in comparison to decision tree and naive Bayes.

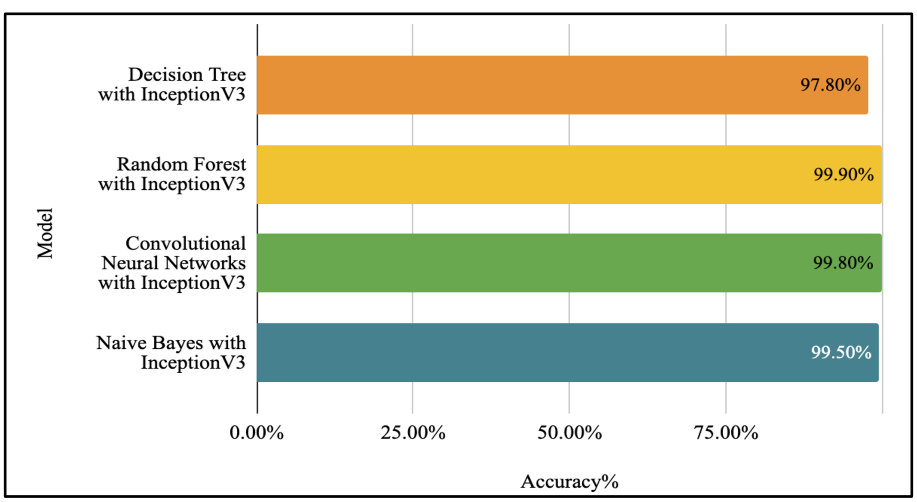

Figure 8. Accuracy comparison of the Inception V3 with decision tree, random forest, CNN, and naive Bayes.

Figure 9 illustrates the precision comparison of the proposed work and shows that Inception V3 with random forest classifier has the highest precision of 0.999 when compared with the decision tree, CNN, and naive Bayes. Figure 10 identifies the comparison in terms of recall and shows the Inception V3 with the random forest as the outperforming model in comparison with other classification models used in the proposed work.

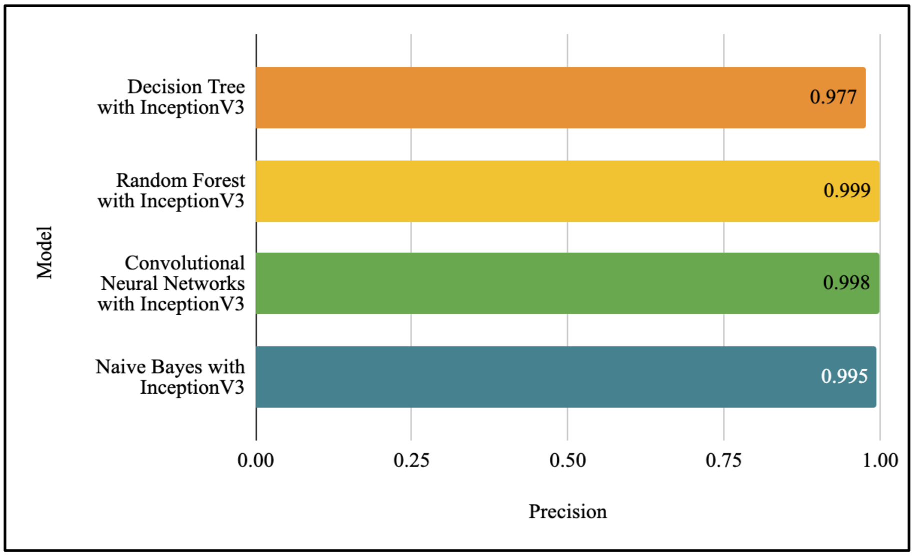

Figure 9. Precision comparison of the Inception V3 with decision tree, random forest, CNN, and naive Bayes.

Figure 11 depicts the result in F1-score and shows that Inception V3 with CNN and random forest have almost similar values of the F1-score, which results in better-performing models when compared with other classification models taken into consideration.

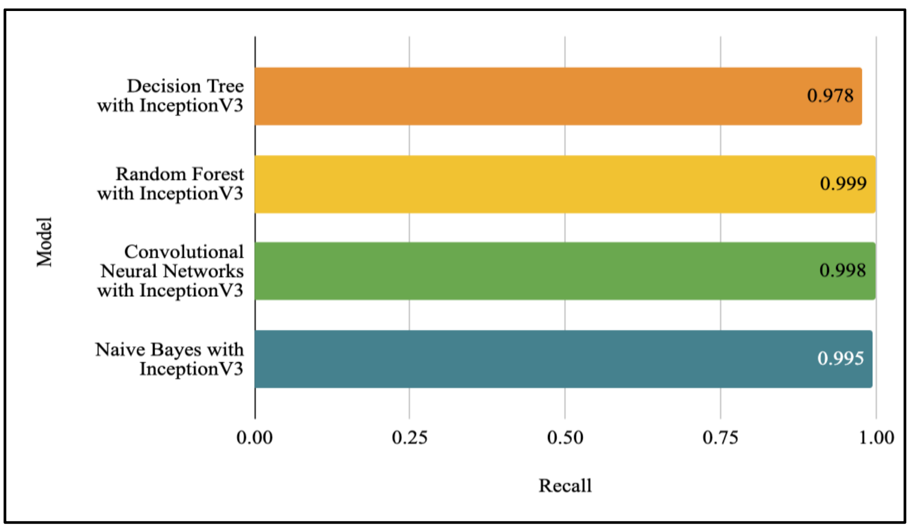

Figure 10. Recall the comparison of the Inception V3 with decision tree, random forest, CNN, and naive Bayes models.

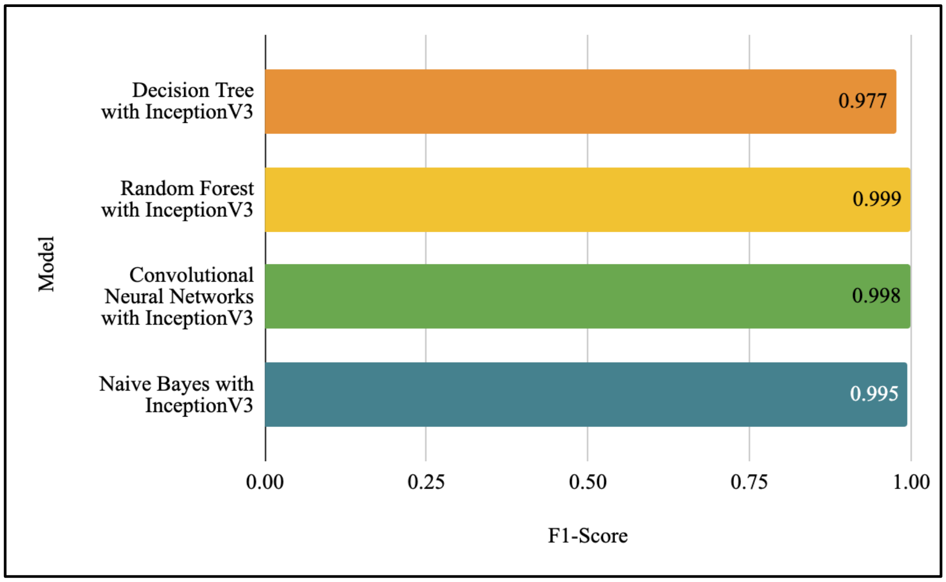

Figure 11. F1-Score comparison of the Inception V3 with decision tree, random forest, CNN, and naive Bayes models.

Figure 12 identifies that both Inception V3 with random forest and CNN have the same value of AUC (Area Under Curve) as 1.00, indicating that both perform best compared to other classification models.

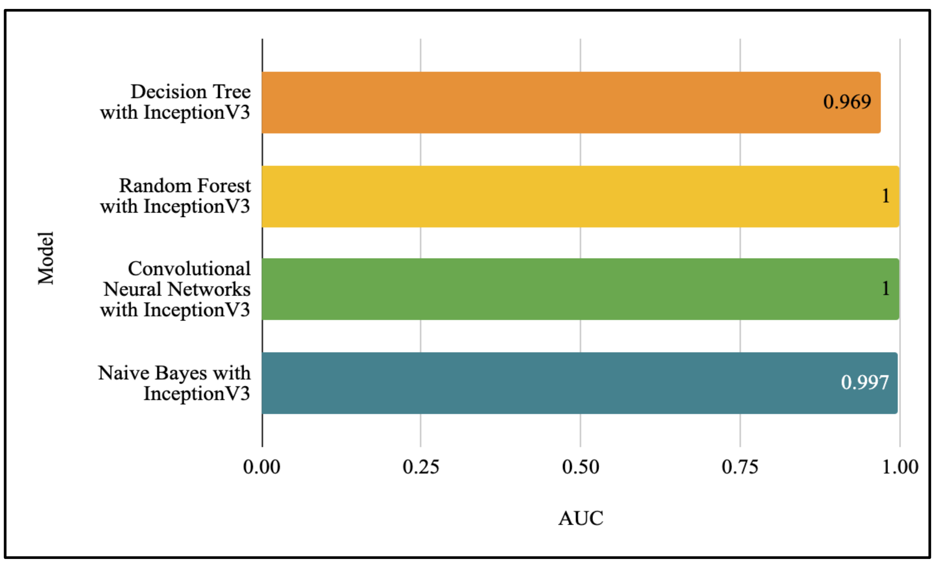

Figure 12. AUC comparison of the Inception V3 with decision tree, random forest, CNN, and naive Bayes classifiers.

The comparison in terms of performance metrics identifies that random forest outperforms all other models, and CNN also shows satisfactory results in comparison to naive Bayes and decision trees.

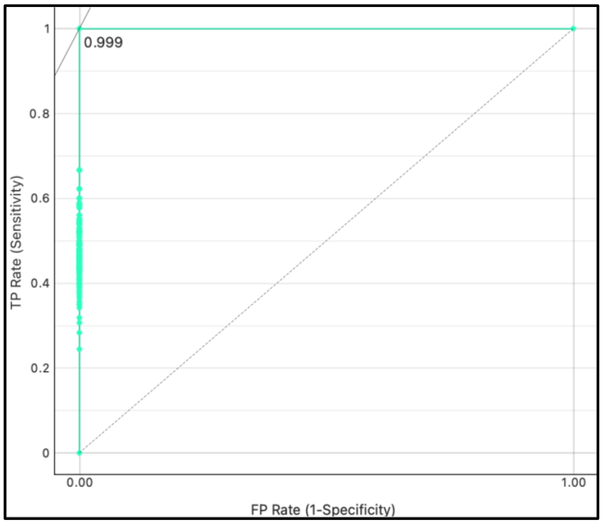

Figure 13. ROC of Inception V3 with neural networks for vitiligo skin disease prediction.

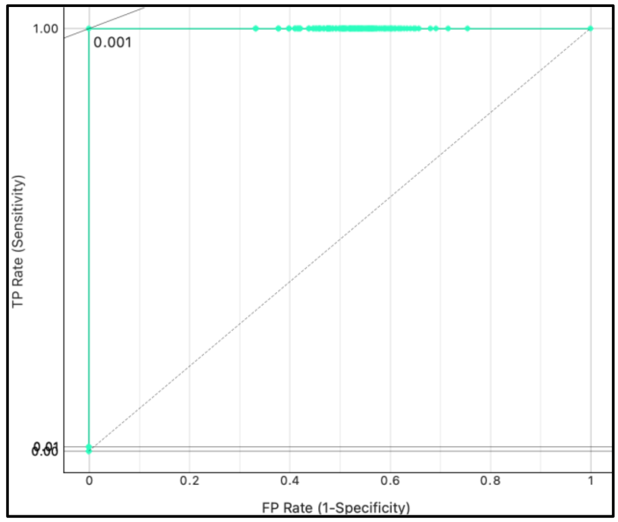

Figure 14. ROC of Inception V3 with neural networks for healthy skin prediction.

Figure 13 and Figure 14 show the ROC (receiver operating characteristics) of the vitiligo skin disease and the healthy skin prediction. Figure 13 depicts the constant increase of the curve towards the top; however, at a certain point, the curve has moved towards the right side of the graph. Similarly, in Figure 14, the constant increase in the curve towards the top of the graph has been seen, which has changed at a certain point with a shift towards the right side of the graph. Both results have shown that Inception V3 with a neural network results in a good prediction outcome for healthy and vitiligo skin diseases.

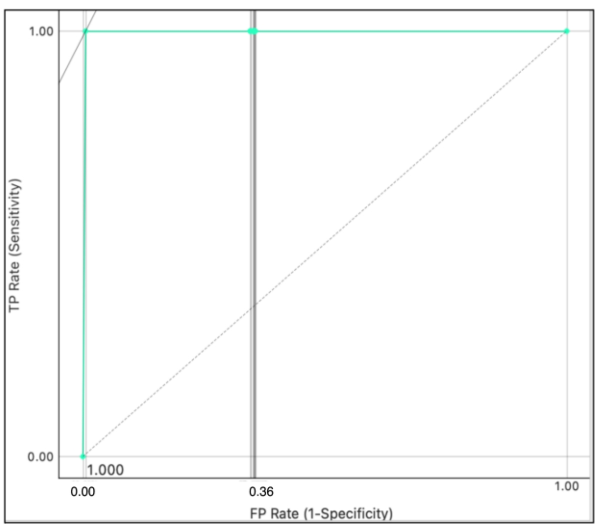

Figure 15. ROC of Inception V3 with naive Bayes classifier for vitiligo skin disease prediction.

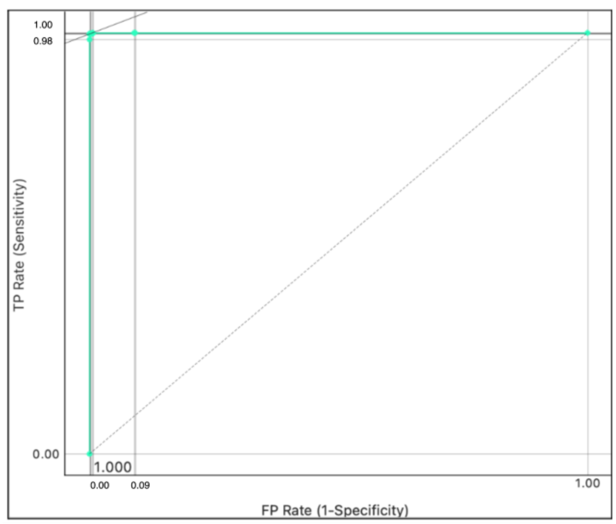

Figure 16. ROC of Inception V3 with naive Bayes classifier for healthy skin prediction.

Figure 15 and Figure 16 show the ROC of the vitiligo skin disease and healthy skin prediction, respectively, by using Inception V3 with a naive Bayes classifier. Both graphs show an instant increase in the curve towards the top left, but later, this curve starts moving towards the right corner of the graph.

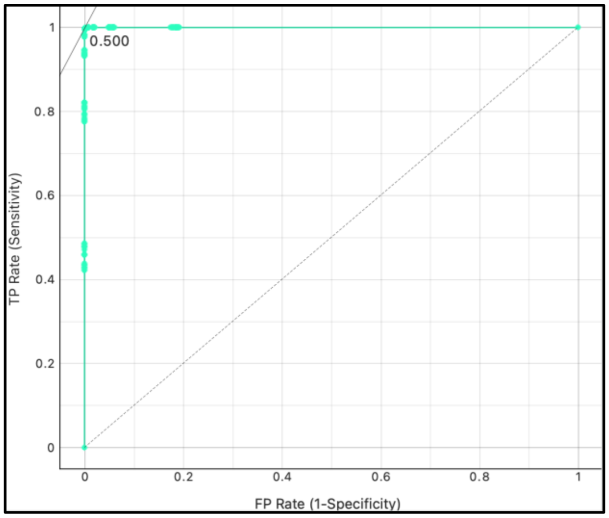

Figure 17. ROC of Inception V3 with random forest for vitiligo skin disease prediction.

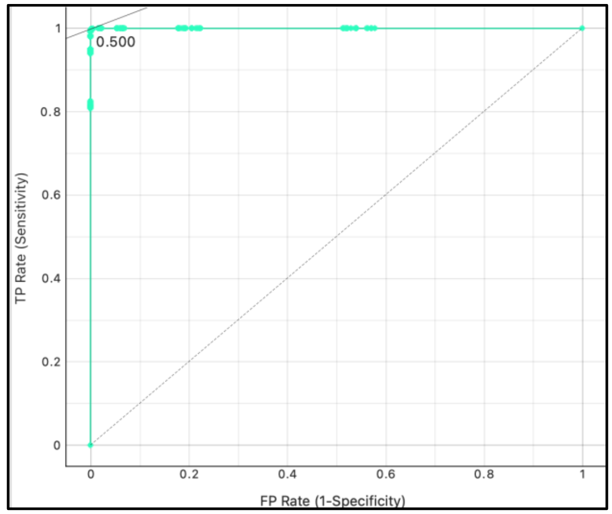

Figure 18. ROC of Inception V3 with random forest for healthy skin prediction.

Figure 17 and Figure 18 show the ROC of the vitiligo skin disease and healthy skin prediction, respectively, using Inception V3 with a random forest classifier. These graphs depict that in the initial stage, both the ROCs started increasing towards the top left, but after peak value, the curve shifted towards the top right of the graph.

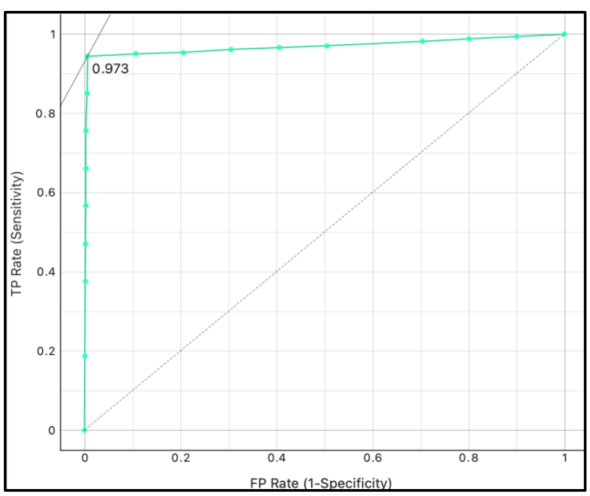

Figure 19. ROC of Inception V3 with decision tree classifier for vitiligo skin disease prediction.

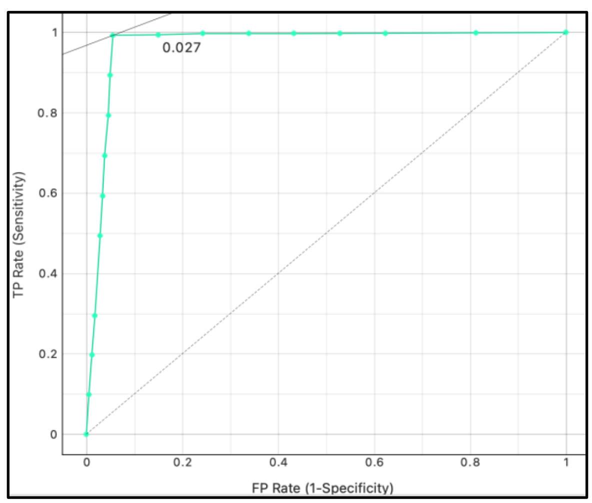

Figure 20. ROC of Inception V3 with decision tree classifier for healthy skin prediction.

Figure 19 and Figure 20 illustrate the ROC of the vitiligo skin disease and healthy skin prediction, respectively using Inception V3 with a decision tree classifier. Figure 19 shows that the ROC has an instant increase towards the top, but later, this curve started increasing towards the top and left side of the graph. Similarly, for the prediction of healthy skin, Figure 20 shows an increase in the curve towards the top and left sides of the graph, resulting in the decision tree being the worst classifier for classifying healthy skin among all the models.

B. The Comparative Analogy of the Proposed Work with the Results Presented in Existing Work

This subsection presents a comparison of the proposed work with the results of state-of-the-art models.

Figure 21 shows an accuracy comparison of the proposed Inception V3 with CNN and Inception V3 with random forest models with the existing models and identifies that the proposed Inception V3 with CNN and random forest models have the highest accuracy.

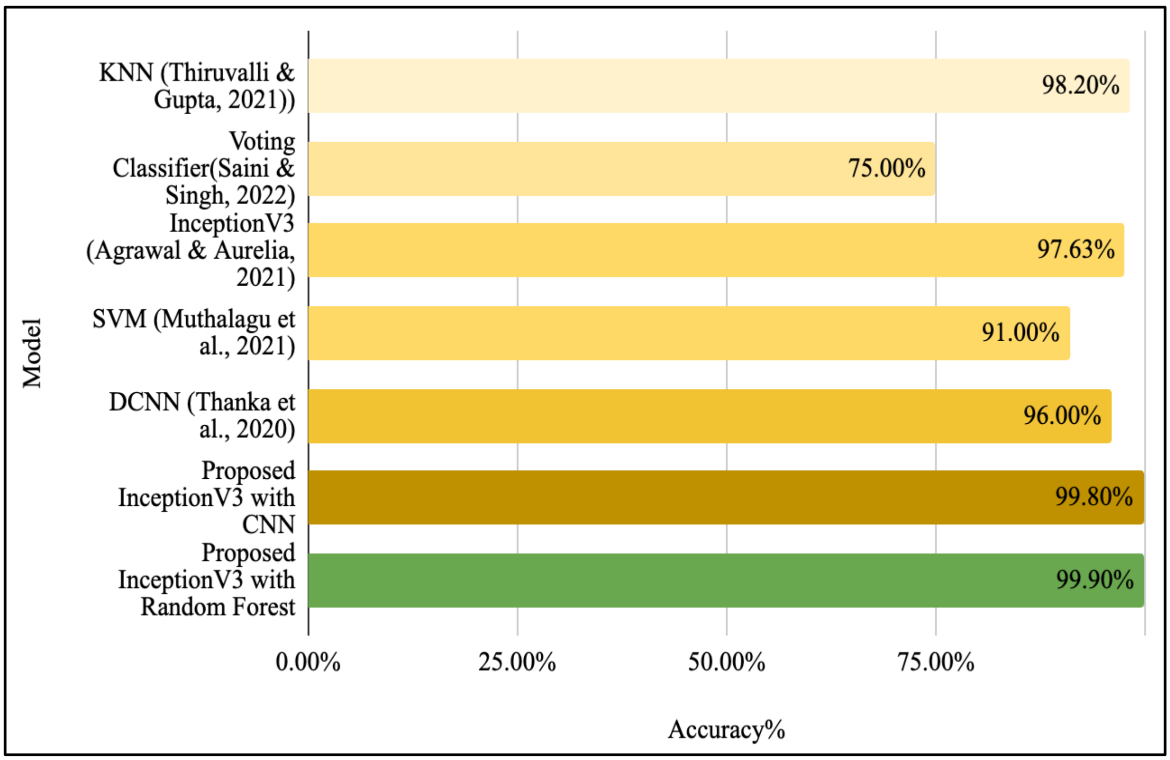

Figure 21. Accuracy comparison of the proposed Inception V3 with CNN and random forest models with the results of existing models.

Figure 22 shows an AUC comparison of the proposed Inception V3 with CNN and Inception V3 with random forest models with the state-of-the-art models and shows that the proposed models have the highest AUC value of 1 in comparison to the existing models.

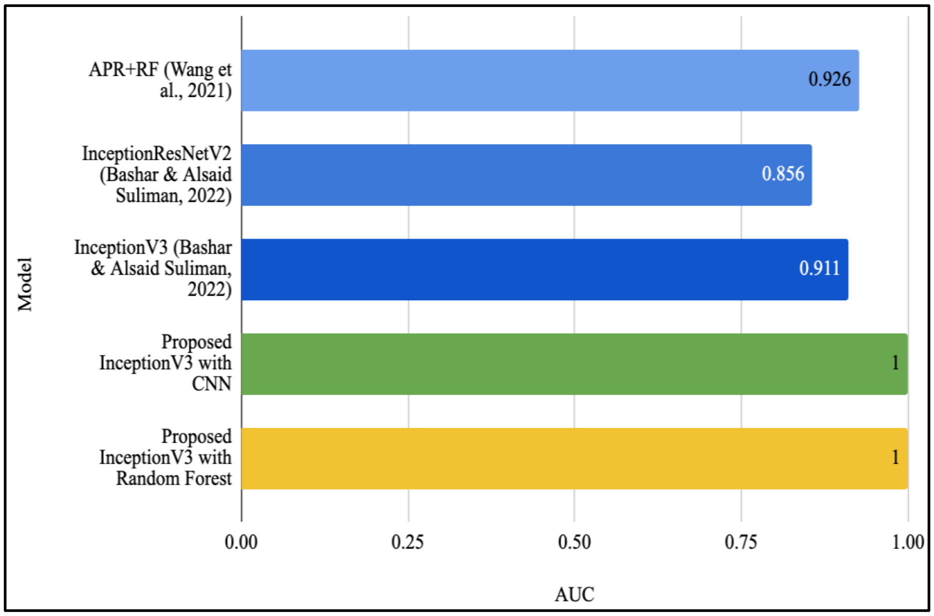

Figure 22. AUC comparison of the proposed Inception V3 with CNN and Inception V3 with random forest models with the results of the existing models.

5. Conclusion and Future Scope

Skin disease is one of the major causes of increased deaths. Vitiligo is a skin disease that contributes to increasing the mortality rate. As per previous studies, it has been identified that almost 0.2% to 1.8% of the population has been affected by this disease all over the globe. This is a major concern that must be resolved to save precious lives and enhance living time. In this work, a DL-based model that utilizes the Inception V3 feature extractor with various classifiers, specifically naive Bayes, random forest, decision tree, and CNN, has been proposed for predicting vitiligo skin disease. The results of the work have been concluded in terms of ROC, accuracy, recall, precision, F1-score, and AUC. Furthermore, the analogy among the results of each model has also been identified and shows that the Inception V3 with random forest outperforms all other models with the highest values of accuracy of 99.9%, precision of 0.999, recall of 0.999, and F1-score of 0.999, along with an AUC value of 1.00. The Inception V3 with CNN model also performs better than the decision tree and naive Bayes models, having values of accuracy of 99.8%, precision of 0.998, recall of 0.998, and F1-score of 0.998, along with an AUC value of 1.00. This work can be helpful in the medical sector by assisting dermatologists in the early identification of vitiligo skin disease. In the future, the dataset for vitiligo can be expanded through data augmentation techniques and extensive primary research, which can enhance the accuracy of predictions and yield precise outcomes.

Conflicts of Interest

No conflicts of interest have been associated with this publication.

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References

Agrawal, N., & Aurelia, S. (2021). Corroboration of skin diseases: Melanoma, Vitiligo & Vascular tumor using transfer learning. In *2021 7th International Conference on Electrical Energy Systems* (pp. 590-592). Chennai, India. https://doi.org/10.1109/ICEES51510.2021.9383682.

Ahammed, M., Mamun, M.A., & Uddin, M.S. (2022). A machine learning approach for skin disease detection and classification using image segmentation. *Healthcare Analytics*, *2*, 100122. https://doi.org/10.1016/j.health.2022.100122.

Awasekar, D. (2021). An enhanced skin disease vitiligo and ringworm recognition android application using image analysis. In *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks* (pp. 1445-1449). Tirunelveli, India. https://doi.org/10.1109/ICICV50876.2021.9388425.

Bashar, N., & Alsaid Suliman, M. (2022). *Vitiligo image classification using pre-trained convolutional neural network architectures, and its economic impact on health care* (Dissertation). Retrieved from https://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-313749.

Guo, L., Yang, Y., Ding, H., Zheng, H., Yang, H., Xie, J., Li, Y., Lin, T., & Ge, Y. (2022). A deep learning-based hybrid artificial intelligence model for the detection and severity assessment of vitiligo lesions. *Annals of Translational Medicine*, *10*(10), 590. https://doi.org/10.21037/atm-22-1738.

Kurama, V. (2020). *A guide to ResNet, Inception v3, and SqueezeNet*. Paperspace Blog. https://blog.paperspace.com/popular-deep-learning-architectures-resnet-inceptionv3-squeezenet/.

Leachman, S.A., Hornyak, T.J., Barsh, G., Bastian, B.C., Brash, D.E., Cleaver, J.E., Cooper, C.D., D'Orazio, J.A., Fujita, M., Holmen, S.L., Indra, A.K., Kraemer, K.H., Le Poole, I.C., Lo, R.S., Lund, A.W., Manga, P., Pavan, W.J., Setaluri, V., Stemwedel, C.E., & Kulesz-Martin, M.F. (2020). Melanoma to vitiligo: The melanocyte in biology & medicine–joint montagna symposium on the biology of skin/panamerican society for pigment cell research annual meeting. *The Journal of Investigative Dermatology*, *140*(2), 269-274. https://doi.org/10.1016/j.jid.2019.03.1164.

Ma, Z., Cai, M., Yang, K., Liu, J., Guo, T., Liu, X., & Zhang, J. (2023). Predicting the risk of autoimmune thyroid disease in patients with vitiligo: Development and assessment of a new predictive nomogram. *Frontiers in Endocrinology*, *14*, 1109925. https://doi.org/10.3389/fendo.2023.1109925.

Mudunuru, V.R., & Skrzypek, L.A. (2020). A comparison of artificial neural network and decision trees with logistic regression as classification models for breast cancer survival. *International Journal of Mathematical, Engineering and Management Sciences*, *5*(6), 1170-1190. https://doi.org/10.33889/IJMEMS.2020.5.6.089.

Neri, P., Fiaschi, M., & Menchini, G. (2020). Semi-Automatic tool for vitiligo detection and analysis. *The Journal of Imaging*, *6*(3), 14. https://doi.org/10.3390/jimaging6030014.

Pal, S., Mishra, N., Bhushan, M., Kholiya, P.S., Rana, M., & Negi, A. (2022). Deep learning techniques for prediction and diagnosis of diabetes mellitus. In *2022 International Mobile and Embedded Technology Conference* (pp. 588-593). IEEE. Noida, India. https://doi.org/10.1109/MECON53876.2022.9752176.

Rushdi, R.A., & Rushdi, A.M. (2018). Karnaugh-map utility in medical studies: The case of fetal malnutrition. *International Journal of Mathematical, Engineering and Management Sciences*, *3*(3), 220-244.

Saini, K., & Singh, S. (2022). Vitiligo disease prediction using K-mean, GLCM and voting classification. In *AIP Conference Proceedings*, *2555*(1), 020013. Mohali, India. https://doi.org/10.1063/5.0109172.

Sharma, R., Kukreja, V., Kaushal, R.K., Bansal, A., & Kaur, A. (2022a). Rice leaf blight disease detection using multi-classification deep learning model. In *2022 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)* (pp.1-5). IEEE. https://doi.org/10.1109/ICRITO56286.2022.9964644.

Sharma, S., Guleria, K., Tiwari, S., & Kumar, S. (2022b). A deep learning based convolutional neural network model with VGG16 feature extractor for the detection of Alzheimer disease using MRI scans. *Measurement: Sensors*, *24*, 100506. https://doi.org/10.1016/j.measen.2022.100506.

Singh, S., & Ramkumar, K.R. (2022). Significance of machine learning algorithms to predict the growth and trend of COVID-19 pandemic. *ECS Transactions*, *107*(1), 5449. https://doi.org/10.1149/10701.5449ecst.

Sonawane, M.M., Albkhrani, A., & Gawali, B.W. (2023). Skin Disease Identification using online and Offline Data Prediction using CNN Classification. *AITC-2023 and CSSP*. https://www.researchgate.net/profile/Aditya-Tripathi25/publication/370230085_AITC_and_CSSP_2023_Proceedings/links/64477ee8d749e4340e3689c6/AITC-and-CSSP-2023-Proceedings.pdf#page=279.

Thanka, M.R., Edwin, E.B., Duela, J.S., & Ebenezer, V. (2020). Automated diagnosis of skin disease multi-class image classification using deep convolution neural network. *Journal of Green Engineering*, *10*(10), 7646-7660.

Wang, J., Luo, L., Ding, Q., Wu, Z., Peng, Y., Li, J., Wang, X., Li, W., Liu, G., Zhang, B., & Tang, Y. (2021). Development of a multi-target strategy for the treatment of vitiligo via machine learning and network analysis methods. *Frontiers in Pharmacology*, *12*, 754175. https://doi.org/10.3389/fphar.2021.754175.

Zhang, L., Mishra, S., Zhang, T., Zhang, Y., Zhang, D., Lv, Y., Lv, M., Guan, N., Hu, X. S., Chen, D. Z., & Han, X. (2021). Design and assessment of convolutional neural network based methods for vitiligo diagnosis. *Frontiers of Medicine*, *8*, 754202. https://doi.org/10.3389/fmed.2021.754202.

Zienab_esam (2022). *Vitiligo Dataset*. https://www.kaggle.com/datasets/zienabesam/vitiligo-dataset.

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