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# Optimized Machine Learning Solution for Skin Cancer Prediction with Bayesian Hyper Parameter Tuning

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## Abstract

Early and precise prediction of skin cancer risk is essential for appropriate clinical intervention and better patient outcomes. Various methods have been proposed for this prediction. In this study, a comprehensive machine learning system is suggested to be used for the classification of skin cancer diseases. The suggested system contains ensemble learning with some of the machine learning algorithms such as Logistic Regression (LR), K-Nearest Neighbours, Decision Tree, Extra Tree and Multi-Layer Perceptron (MLP). The soft voting ensemble and CatBoost classifier combine these enhanced base learners to improve classification performance. To overcome data imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) is used, and each model's hyperparameters are fine-tuned via Bayesian optimization. The models showed varied levels of performance, with Extra Tree having the greatest accuracy of 95%, followed by MLP at 93% and KNN at 91%. Decision Tree and Logistic Regression demonstrated reasonable accuracy of 87% and 82%, respectively. Confusion matrix examination revealed that some models, despite having lower accuracy, had a high sensitivity in identifying affirmative cases. The performance of most models improved after applying Bayesian optimization. Extra Tree had the highest accuracy of 97%, while MLP, KNN, and Decision Tree were close behind with 94%, 91%, and 90% accuracy, respectively. Logistic Regression achieved 81% accuracy but had the highest precision. Confusion matrix analysis indicated that optimization improved model performance, reducing incorrect classifications and enhancing class separation.

## Keywords
Bayesian Optimization, CatBoost, Ensemble Voting, Machine Learning, Skin Cancer Prediction

## 1. Introduction
Skin cancer is one of the most widespread types of diseases worldwide and a major health concerns in the society. Some of the factors that have contributed to its ever-increasing populations are long term exposure of UV, alterations in the environment, and alteration in lifestyle. Early diagnosis and accurate diagnosis are vital in reducing treatment costs, as well as improving patient survival rates. Despite the improvement of imaging and dermatology, the majority of cases are still undetected until further research conducted which decreases treatment and leads to negative outcomes. This necessitates the need to find a reliable and automated diagnostic procedure that may assist physicians in detection of cancerous lesions in their early stages of development. Especially, the important aspects of conventional diagnosis methods are the visual examination and dermoscopy of which qualified dermatologists are the evaluators. These evaluations are unreasonable and prone to inequalities among different technicians, but, high accuracy can be achieved when competent technicians are involved. In some cases, the difficulty of accurate identification is compounded by a few modifications in the lesion’s color, shape and textures.

Nowadays, medical components have been introduced the application of machine learning (ML) as a powerful means that can help in consistent and unbiased decision making. Because, manual inspection takes too much time and may not be particularly effective when applied to populations of screening needed in context of some illness. Machine learning models can enhance diagnostic speed, consistency and accuracy by uncovering the associations that can be very difficult to record using traditional methods. Traditional algorithms, such as Multi-Layer Perceptron (MLP), Decision Trees, K-Nearest Neighbors (KNN) and Logistic Regression have assisted in identifying the skin cancer symptoms. However, the problems such as overfitting, noise, missing values, and imbalance of the data set may limit the effectiveness of these models and reduce their predictive validity with a variety of patient categories. Ensemble learning enhances the diagnosis of skin cancer by combining models which include the Logistic Regression, KNN, Extra Trees, and MLP to increase accuracy, decrease bias, and capturing the complex patterns. SMOTE balances the data, whereas the Bayesian optimization standardizes hyperparameters to make its data more effective. CatBoost and soft voting are complimentary in sensitivity and specificity. The use of ensemble-based frameworks contributes to the factual, interpretive, and clinically useful scaling of early skin cancer diagnosis.

## 2. Literature Review

Skin cancer is still among the most prevalent cancers, and its increasing prevalence is rising worldwide. With exposure to ultraviolet (UV) radiation, environmental factors, hereditary factors, as well as with the change in lifestyles, there was a rise in the incidence of melanoma and non-melanoma skin cancers. (Tembhurne et al., 22023; Dildaret al., 2021). The detection of cancer in the skin at an earlier stage and with more accuracy is vital as it is associated with better results in the treatment and better survival rates for the patient. In this case, machine learning (ML) with deep learning (DL) have achieved significant attention due to their potential in improving diagnostic accuracy and helping clinicians to achieve a clinical decision (Murugan et al., 2021; Imran et al., 2022). Recent developments in artificial intelligence (AI) have made the creation of highly precise diagnostic tools essential for the future. These systems rely on a number of data sources such as 3-D images, patient metadata and histopathology images. Several classification methods including transfer learning, consideration processes, ensemble learning and convolutional neural networks (CNNs) have shown promising results for skin cancer classification. CNN architectures were studied in this, who compared how well preprocessing works to enhance model adaptation (Javaid et al., 2021; Bechelli et al., 2022). The enhanced classification between model shifting by several combination of transfer learning using pre-trained CNN model. Using Hellig's deep neural network pipeline introduced the Deepskin model, which demonstrated a valuable classification performance across all the data sets. The goal of several studies has been to increase the accuracy of unbalanced data sets by augmenting information through further training (Ali et al., 2021; Gururaj et al., 2023). This work focused on deep learning for effective classification, while other work focused on the usage of transfer learning and data augmentation for enhancing detection of melanoma (Ashraf et al., 2020; Yousra et al., 2023). The proposed work used segmentation-based transfer learning along with hybrid classifiers for more accurate identification of melanoma (Dandu et al., 2023).

Proposed a novel combination model, which varies the deep feature extraction with machine learning model with the ability to successfully resolve imbalance of the classes in datasets (Verma et al., 2024). This study contains the recent developments in lesions identification and classification, which there are some issues like inconsistency of a dataset or labelling issues (Hasan et al., 2023). This paper stated a multi-level classification technique to overcome such obstacles for enhancing the effectiveness of multi-class classification (Hameed et al., 2020). The presented a GAN based Data augmentation approach which is used to tackle the class imbalance and enhance the performance of classifiers (Suet et al., 2024). They have proposed the hybrid methods which encompass ML approaches combining ensemble as well as transfer learning methods to enhance melanoma classification (Thanka et al., 2023). They are shown the effectiveness of techniques like attention and multimodal fusion in the fusion between the image and the metadata. The authors assembled the PAD-UFES-20 dataset containing clinical information of participants and also smartphone-captured images that can serve as a proper baseline for multimodal research (Pacheco et al., 2020). For histological diagnosis, proposed the visually noticeable deep learning model, which is increased the trust of physicians by the model visualization grade (Jiang et al., 2021). They found that integration of comprehensible machine learning methods can help support psychologists in making decisions in real world (Vidya and Karki 2020). However, existing research findings for skin cancer diagnosis based on structured clinical data have limitations such as class imbalance, insufficient hyper-parameter tuning and very less model generalization. Also, traditional classifiers often suffer from limited availability of malignancy data. And, manual or grid search optimization methods usually lack at identifying the best model parameters that improve the predicted accuracy and sensitivity. Therefore, it is suggested to use a combination of Bayesian optimization, MLP and SMOTE. Bayesian optimization is identified to be an adaptive training for hyperprameter running, MLP for non-linear feature learning and SMOTE as a class balancing technique. Unlike traditional optimization methods, with the help of probabilistic models, Bayesian optimization is able to sample the hyper-parameter space efficiently. In turn, it could produce the optimal combination of hidden layer, activation function, learning rate and regularization parameter settings. As a consequence, the model performance and convergence stability is improvised. Additionally, stratified cross-validation serves as a valid evaluation for the model. By simultaneously improving sensitivity, generalization and overall predictive ability, our method could overcome the drawbacks of the previous approaches and create a skin cancer risk prediction system of higher accuracy and reliability.

## 3. Dataset Description

For this investigation, the skin cancer dataset was gathered via the Kaggle platform. The data set contains in Figure 1 the structured data that are related to the health records with 18 columns (features) and more than 31,9796 rows. Each row shows the lifestyle and health information of a single individual. The features contain a combination of demographics, behavioral characteristics and medical characteristics which can be used for detecting skin cancer. Machine learning models are developed using the data set that will be used for training, typically comprises between 70 and 80 percent of the total data set, by identifying correlations and patterns between the features contained in the data that are intended to identify the health condition (in this case, skin cancer).It is the testing data set made up of the remaining 20% to 30% is used to evaluate how well the trained algorithm using machine learning works and generalizes to new data set.

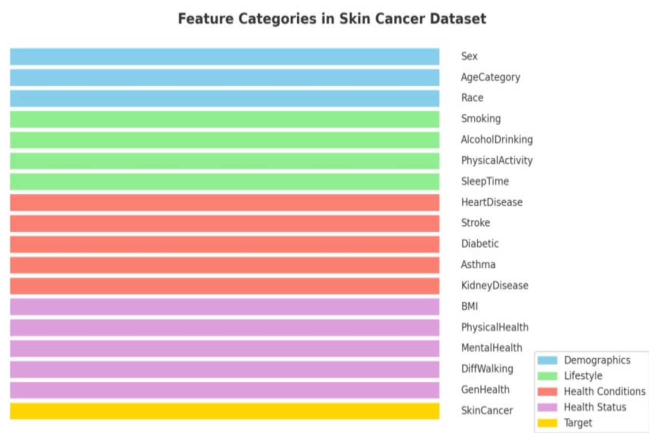


Figure. 1 Dataset Features

## 4. Methodology

Figure 2 indicates that the proposed methodology would start with the collection of a systematic clinical data set having a number of variables related to health. The prepossessing steps that are followed to get rid of the imbalance between the malignant and non-malignant cases include the train-test division, normalizing the data using Standard Scaler, and class balancing using the Synthetic Minority Over-sampling Technique (SMOTE). Our method involves implementing five machine learning models i.e. Logistic Regression (LR), K-Nearest Neighbours, Decision Tree, Extra Tree and Multi-layer Perception (MLP). Consequently, a fine-tuning of the hyperparameters of every model is applied using Bayesian Optimization to enrich the model and in turn improvise the performance. Finally, a soft voting ensemble is then used to aggregate these refined models so that they will have maximum prediction capability. Then, in order to evaluate the classifiers, measures such as accuracy, precision, recall and F1 score are estimated. Thus, it is believed that the essential predictions can enable cancer classification of skin cancer, and the ultimate objective can be achieved to enhance early diagnosis and medical decision-making.

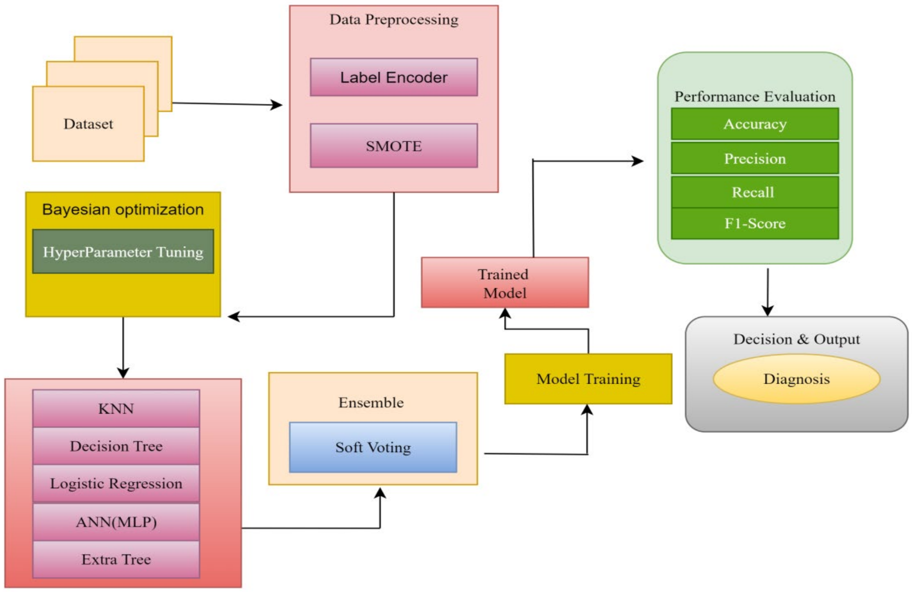


Figure. 2 Skin Cancer Detection

There are five machine learning models employed to categorize skin cancer in the present study. The probability of cancer is measured with the Logistic Regression (LR) by means of a sigmoid taking the form of a simple and powerful linear model. Similarly, K-Nearest Neighbors (KNN) method at the decision of classifying data by the comparison of the data with the $k$ neighboring locations is used to establish spatial patterns. While Extra Trees algorithm attempts to enhance the process of generalization by using random decision trees but on the other hand, Decision Trees produce interpretable structures by dividing the data based on the importance of the feature. The Multi-Layer Perceptron (MLP) model of deep learning is used to represent non-linear interactions by forward and backward propagations. To top it off, a soft voting ensemble along with CatBoost is used to strengthen the overall prediction through optimization and hence to increase the classification accuracy. Then, the ensemble model is trained on SMOTE-balanced data and optimized with Bayesian parameter to forecast skin cancer.

## 5. Results & Discussion

Following the experimental design, the performance of all models was evaluated in four phases which included, performance of all models before SMOTE and after SMOTE, as well as before optimization and after optimization. First, models were considered with an unbalanced dataset to calculate baseline performance. Balancing the classes and enhancing generalization was then done by means of SMOTE. Models were then evaluated using default settings and then Bayesian Optimization was used to optimize hyperparameters and enhance accuracy, recall and F1-score. The consecutive comparison of this technology shows that data balancing and optimization can be used to improve the performance of skin cancer prediction.

### 5.1 Before SMOTE

Table 1 presents model performance before applying SMOTE. Despite the class imbalance, models perform well, with Logistic Regression and ANN(MLP) achieving the highest Recall (1.00 and 0.99), ensuring minimal false negatives. Decision Tree shows comparatively lower Accuracy and F1-Score, indicating a need for further optimization or imbalance handling.

Table 1. Before Applying SMOTE

| Algorithm | BEFORE SMOTE | | | |
|---|---|---|---|---|
| | Accuracy | Precision | Recall | F1-Score |
| Logistic Regression | 0.91 | 0.91 | 1.00 | 0.95 |
| KNN | 0.89 | 0.91 | 0.98 | 0.94 |
| Decision Tree | 0.84 | 0.92 | 0.91 | 0.91 |
| Extra Tree | 0.87 | 0.91 | 0.95 | 0.93 |
| ANN(MLP) | 0.90 | 0.91 | 0.99 | 0.95 |

In Figure 3 Graph, it can be seen that all the models exhibit excellent results overall and ANN (MLP) as well as cancer regression appear to be highest in terms of recall results. Decision Tree and Extra Tree, unlike the others, exhibit worse Accuracy and Recall therefore implying the possibility of an issue with sensitivity to the class imbalance. Based upon this performance comparison, it is possible that the dataset has some kind of imbalance in classes and therefore in the future adoption of SMOTE (Synthetic Minority Over-sampling Technique) is to be employed in order to enhance the generalization of the model especially that of the minority classes.

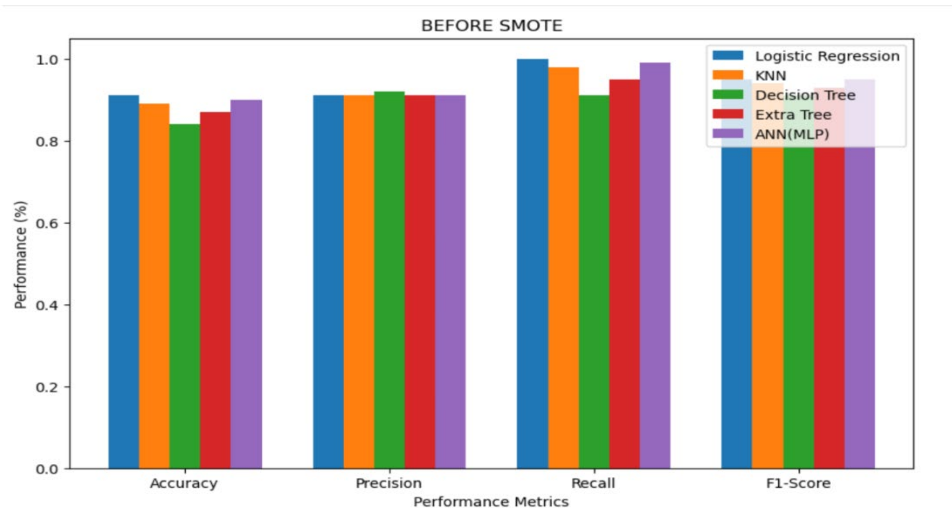


Figure 3. Comparative Analysis: Before SMOTE

## 5.2 After SMOTE

Table 2 shows that there was a decline in the performance of various classifiers that included ANN, KNN as well as logistic regression after they were subjected to SMOTE data augmentation. This reduction occurs because the creation of synthetic examples that occur with SMOTE through interpolation between the occurrences of the minority classes can create overabundant or noisy instances near the boundaries between classes. As a result, it means that models relying on linear/distance-based separability assumptions are prone to these synthetic samples causing poor generalization and flawed classification. In addition to this, the adaptation to artificial patterns instead of true class characteristics could be due to the distortion of the actual data distribution by the modified feature space. Conversely, since they are not as sensitive to the data distribution and can be less affected by the issue of the class imbalance in the case of automatic oversampling, tree models such as Decision Tree or Extra Tree remained stable.

We initially assumed that when SMOTE was used, all models would reach better accuracy and performance, but after comparing the results, we have found that some classifiers have depreciated, which prompted us to reach the above conclusion.

Table 2. After applying for SMOTE

| **Algorithm** | **AFTER SMOTE** | | | |
|---|---|---|---|---|
| | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
| **Logistic Regression** | 0.66 | 0.98 | 0.54 | 0.70 |
| **KNN** | 0.74 | 0.95 | 0.68 | 0.79 |
| **Decision Tree** | 0.82 | 0.92 | 0.91 | 0.91 |
| **Extra Tree** | 0.83 | 0.92 | 0.88 | 0.90 |
| **ANN (MLP)** | 0.72 | 0.97 | 0.60 | 0.74 |

Figure 4 shows that all classifiers' overall performance improved, especially in Recall, following the application of SMOTE, suggesting improved handling of class imbalance. The most balanced model after SMOTE is the Decision Tree, which has the best Recall and F1-Score, while Logistic Regression has the highest Precision.

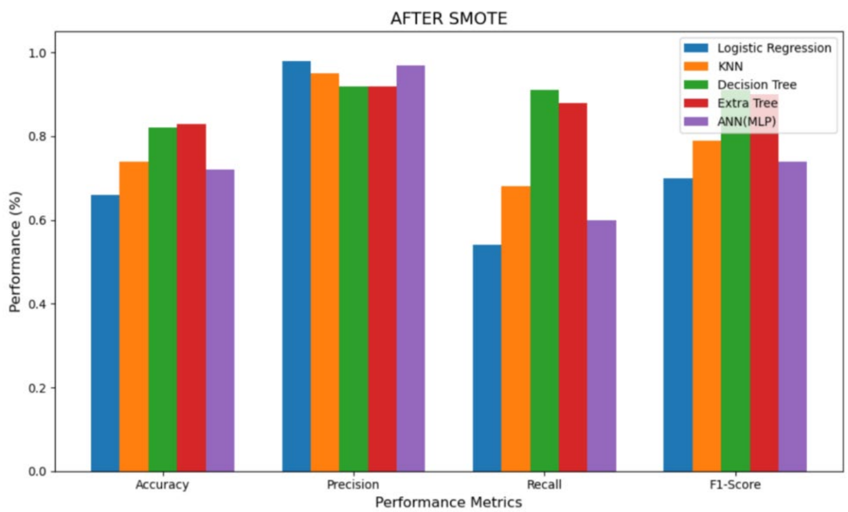


Figure 4. Comparative Analysis: After SMOTE

## 5.3 Before Optimization

Table 3 Indicates Without Bayesian Optimization model performance. Extra Trees and ANN (MLP) performed even better but were constrained by default settings, Logistic Regression and Decision Tree had disproportional precision and recall. Generalization and balance were improved by tuning various learning rate parameters, tree depth, neighbors and regularization after optimization. Extra Trees recorded the highest accuracy (96%) and ANN (MLP) the best F1-score (0.97), thus indicating the usefulness of Bayesian Optimization.

Table 3. Without Bayesian Optimization

| Algorithm | WITHOUT BAYESIAN OPTIMIZATION | | | |
|---|---|---|---|---|
| | Accuracy | Precision | Recall | F1-Score |
| Logistic Regression | 0.82 | 0.91 | 1.00 | 0.95 |
| KNN | 0.91 | 0.91 | 0.98 | 0.94 |
| Decision Tree | 0.87 | 0.92 | 0.91 | 0.91 |
| Extra Tree | 0.95 | 0.91 | 0.95 | 0.93 |
| ANN(MLP) | 0.93 | 0.91 | 0.99 | 0.95 |

The model's performance without Bayesian optimization is displayed in Figure 5. The best accuracy is attained by Extra Tree, while the best recall and F1-score are maintained by Logistic Regression. Although the models' precision is generally consistent, hyper-parameter optimization should be improved to further increase performance.

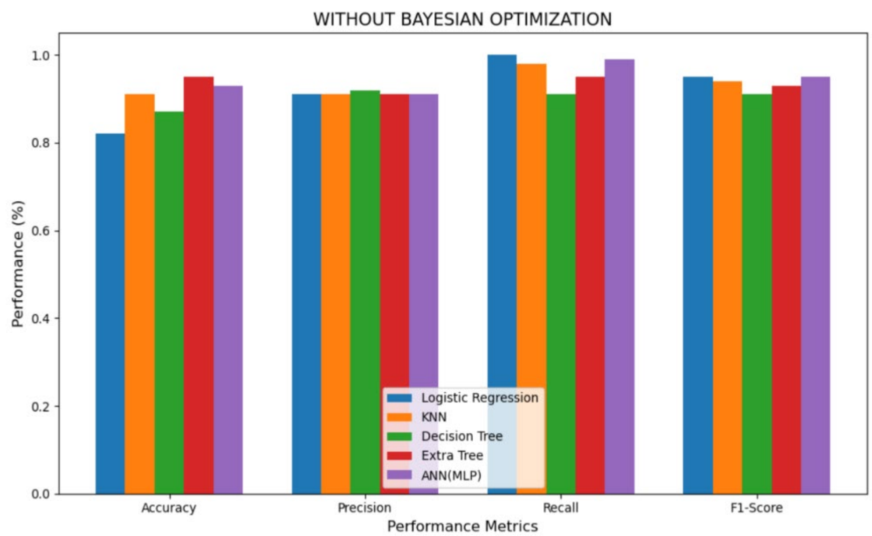


Figure 5. Comparative Analysis: Without Bayesian Optimization

## 5.4 After Optimization

Table 4 provides the outcomes of the Bayesian Optimization method, which effectively optimized the hyperparameters of every model with the help of the Gaussian Processes. Logistic Regression with its linear nature had 96% accuracy. The neighbor and distance adjustments gave KNN 91 percent accuracy and a recall of 96 percent. The Decision Tree had an accuracy of 90 percent and precision and recall of 95 and 92 percent respectively. Extra Trees performed best (96% accuracy) and optimized ANN (MLP) performed well with 94% accuracy, 98% precision and best F1-score (0.97).

Table 4. With Bayesian Optimization

| Algorithm | WITH BAYESIAN OPTIMIZATION | | | |
|---|---|---|---|---|
| | Accuracy | Precision | Recall | F1-Score |
| **Logistic Regression** | 0.81 | 0.96 | 0.81 | 0.88 |
| **KNN** | 0.91 | 0.93 | 0.96 | 0.95 |
| **Decision Tree** | 0.90 | 0.95 | 0.92 | 0.94 |
| **Extra Tree** | 0.96 | 0.90 | 0.84 | 0.87 |
| **ANN(MLP)** | 0.94 | 0.98 | 0.95 | 0.97 |

Bayesian optimization improves model performance across the majority of metrics, as seen in Figure 6. While Logistic Regression is superior in precision, Extra Tree attains the greatest Accuracy, Recall, and F1-Score. All things considered, Bayesian Optimization improves models and increases their capacity for prediction.

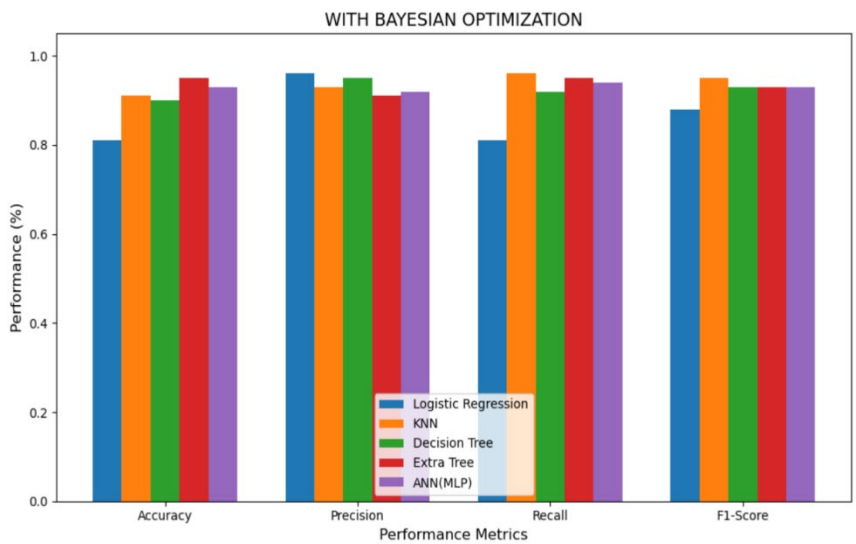


Figure 6. Comparative Analysis: With Bayesian Optimization

## 5.5 Soft Voting Ensemble

As can be seen in Table 5, the Soft Voting Ensemble was able to get balanced and enhanced performance because of the successful integration of different classifiers. Extra tree classifier was found to have the best accuracy (0.96) and precision (0.95) with high class discrimination. The results were also consistent and stable with Logistic Regression and Decision Tree. On the whole, the ensemble was more generalized and reliable than individual models.

Table 5. Soft Voting Ensemble

| **Algorithm** | **Soft Voting Ensemble** | | | |
|---|---|---|---|---|
| | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
| **Logistic Regression** | 0.94 | 0.90 | 0.92 | 0.91 |
| **KNN** | 0.93 | 0.86 | 0.92 | 0.89 |
| **Decision Tree** | 0.94 | 0.93 | 0.85 | 0.89 |
| **Extra Tree** | 0.96 | 0.95 | 0.92 | 0.93 |
| **ANN(MLP)** | 0.93 | 0.90 | 0.87 | 0.88 |

The results of the application of Soft Voting Ensemble approach in performance of various algorithms are compared in Figure 7. Extra Tree classifier is the best and accurate and this means that it is doing well on the overall performance. Logistic Regression Decision Tree are equally very competitive on measures. KNN and ANN (MLP) perform poorly averagely with regard to recall and F1. In all, the ensemble approach increases the consistency and reliability of classification.

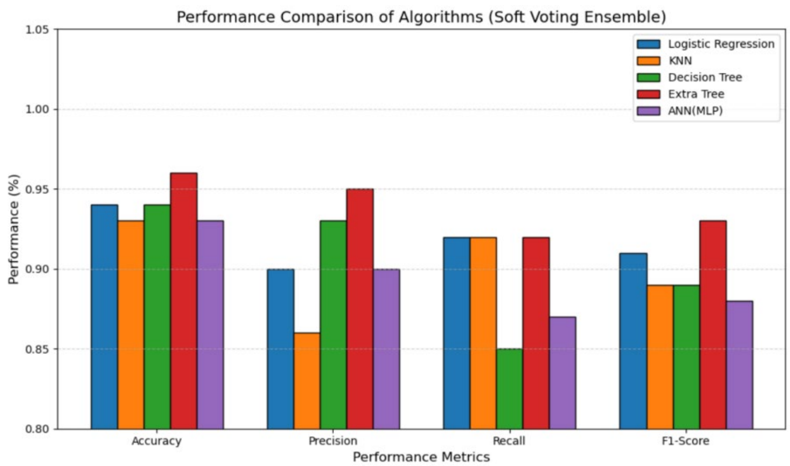


Figure 7. Comparative Analysis: Soft Voting Ensemble

## 6. Conclusion and Future Work

Skin cancer identification is critical for reducing mortality rates, facilitating early treatment, and limiting long-term consequences. The diagnostic approaches, in turn, are time-consuming, costly, and dependent on the specialists. The recent research relied on AI methods that developed an automated, high-accuracy risk prediction framework for the skin-cancer prediction. The attributes such as BMI, genetic medical history, or lifestyle symptoms explain the importance of structural characteristics to predict the development of illnesses. In our work, a total of five algorithms were put together for the intended purpose. The five models viz. Logistic Regression, KNN, Decision trees, Extra trees, and MLP. The models have been evaluated both with and without SMOTE, and no improvement was identified. Most metrics—accuracy, recall, and F1-score were reduced following SMOTE, whereas precision increased slightly in some cases, demonstrating that oversampling did not improve overall performance. When tested before and after Bayesian Optimization, most models, including KNN, Decision Tree, and ANN, demonstrated higher accuracy, precision, and F1-score. This illustrates that Bayesian Optimization can significantly enhance model performance and stability. Overall, the findings show that SMOTE had a modest influence, whereas Bayesian Optimization was useful in fine-tuning the models for improved predictive From the extensive implementation, the Extra Trees classifier is identified to be the most accurate one. In future, we can apply the model to more effectively diagnose patients in the initial stage and regulate their care The next generation of the model can be augmented with deep optimization techniques, interpretable AI systems, and multi-data modalities, such as clinical images. Further expansion of the system to a federated learning setup would also help to provide privacy-sensitive and scalable distribution across the healthcare organizations.Such as clinical images. Extending the system into a federated educational environment would also enable privacy-preserving and scalable distribution across healthcare organizations.

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## Biographies

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