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Research Article

A Comparative Study of Machine Learning Algorithms for Skin Cancer Detection

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Abstract: The skin is the largest organ in the human body, covering an area of around 20 square feet. Our skin keeps us safe from germs and the environment, helps us regulate our body temperature, and gives us the ability to feel touch, heat, and cold. More than 95 percent of all skin cancers are caused by ultraviolet (UV) radiation. UV radiation is emitted by the sun, although it is unrelated to sunshine or heat, as many people believe. The key factor that causes skin cells to become cancer cells is exposure to UV radiation. Overexposure to UV radiation causes almost all skin cancers (about 99 percent of non-melanoma skin cancers and 95 percent of melanoma). Sunburn has been shown to play a significant role in the development of melanoma, the most dangerous of the three most common types of skin cancer. According to research, UV rays can alter a gene that suppresses tumours, increasing the risk of sun-damaged skin cells turning into skin cancer. Melanoma is the worst form of skin cancer and one of the most common cancers. Melanoma rates are quickly increasing, particularly in young people and have increased in the previous 30 years, despite the fact that cancer rates for other prevalent cancers have decreased. Melanoma is highly treatable if found early. While late-stage melanoma treatments are quickly improving, prevention and early detection remain the best treatment options. Our study delves into the critical realm of skin cancer detection with the aim of evaluating the efficacy of various cutting-edge machine learning algorithms including Random Forest, Support Vector Machine, and CNN is exploring skin cancer patterns. Through careful examination, utilizing metrics like accuracy, precision, and recall, we highlight the superior performance of SVC and CNN. Our research not only contributes to the ongoing studies in skin cancer detection but also underscores the potential of advanced computational strategies in augmenting preventive healthcare strategies.

Keywords: Melanoma, Skin Cancer, Random Forest, Convolutional Neural Network, Support Vector Machine, Decision Tree

Introduction

Skin cancer is characterised as the unchecked growth of abnormal cells in the epidermis, the skin's top layer, because of unrepaired DNA damage that results in mutations. Skin tumours are created because of these alterations, which allow skin cells to multiply quickly. The most prevalent types of skin cancer (MCC) include Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), melanoma, and Merkel cell carcinoma. Skin tumours are a very common form of tumour. In general, there are two types of tumour cells in the skin: Malignant melanoma, which occurs infrequently and is fatal; and nonmelanoma skin cancer, which occurs frequently but is not fatal. Skin tumour cells can occasionally be a sign of malignant melanoma. It is the least prevalent and most deadly type of skin tumour cells. This type of skin cancer is responsible for

75% of deaths in the United States (Revathi and Chithra 2015). Around the world, 2 to 3 million people are anticipated to receive a skin cancer diagnosis each year (WHO, 2020). Moles are skin growths that are usually brown or black in colour. Moles can appear alone or in clusters anywhere on the skin. Moles form when skin cells cluster together instead of spreading evenly across the surface. Melanocytes are the cells that produce the pigment that gives skin its natural colour. Moles can darken after sun exposure, during adolescence, and during pregnancy. Overexposure to the sun is linked to the majority of skin malignancies. Certain factors can raise the likelihood of acquiring skin cancer. These are referred to as risk factors. The presence of one or more risk factors does not guarantee that a person will develop skin cancer. The sooner cancer is identified, the more likely it is to be cured. However, if it is not recognised early, it may spread to other parts of the body, causing irreversible damage.

It's difficult for dermatologists to discern the difference between a benign and a malignant mole, making it difficult to come up with a suitable classification rule. Dermatologists use a few strategies to improve categorization accuracy, such as the ABCD rule (Atypical, Border, Colour, and Diameter), although human knowledge is still essential (Franz *et al*., 1994; Das *et al*., 2021). ML has the potential to help in skin cancer early detection. For instance, deep convolutional neural networks can assist in the creation of a system for assessing skin images in order to detect skin cancer (Saravana Kumar *et al*., 2021). Early identification is essential for successful skin cancer therapy and better outcomes. In order to save lives and minimise the financial and physical demands on patients, automated procedures that can identify the illness quickly are needed. Professionals are capable of diagnosing cancer properly, but due to their restricted availability, they are not always available (Keeney *et al*., 2009). The aim of our work is to analyse and comprehend the best out of five different classification algorithms using a dermatologically attested dataset (Schierbeck *et al*., 2019; Holger *et al*., 2018a). A number of researches and implementations have been carried out with respect of various types of cancer over the years. The graph shown in Figure 1 indicates the number of research papers and articles published in this field from 2012 up until the month of May in 2022 (Gutman *et al*., 2016; Marchetti *et al*., 2018).

Comparative Analysis on Existing Works

Advancing technologies in the world today has led to a splurge of technical advancements in medical diagnosis. Skin cancer detection and classification is one such major field which has evolved for the better with the incorporation of technology. With different types of Machine Learning (ML) and Deep Learning (DL) algorithms available for object detection and image segmentation, diagnosis of skin cancer at the preliminary level can be complemented by using these algorithms. Some of the existing works and research in this field are listed in Table 1.

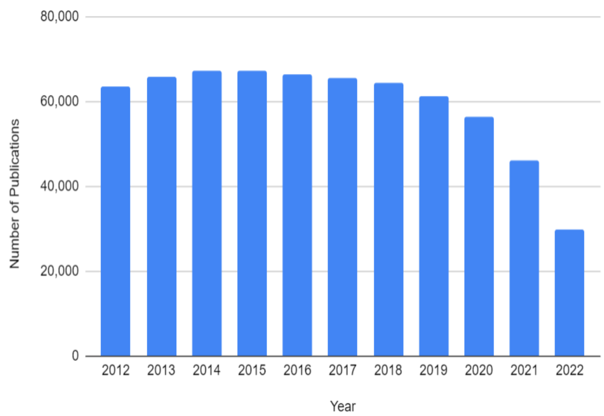

Fig. 1: Published articles with the title skin cancer detection

Table 1: Literature Survey

S. No	Dataset Used	Methodologies Used	Metrics used	Interpretation of Results
Toğaçar *et al.* (2021)	ISIC Cancer Dataset	MobileNet V2 Model for classification with Spiking Neural Network (SNN)	Precision Accuracy F1-score Sensitivity Specificity	The dataset was restructured using the autoencoder approach to improve usage. Two datasets were used to train the MobileNetV2 model at first, and feature sets were acquired to increase its effectiveness
Thurnhofer-Hemsi and Domínguez (2021)	HAM10000 dataset - more than 10,000 images spread over 7 different classes	GoogLeNet Inception V3 DenseNet201 MobileNetV2 Plain and Heirarchical Clasifiers are used	F-Measure Accuracy Recall Precision	*Plain Classifier* Most neural networks had decent training accuracy, but DenseNet201 stands out from the competition by correctly classifying 96% of the inputs. *Hierarchical Classifier* With more than 96% accuracy, DenseNet201 once more produces the best results in the training set
Alizadeh and Mahloojifar (2021)	ISIC 2016 ISIC 2019 PH2	CNN Classification - Model Proposed by Author (Batch Normalization) CNN Classification - VGG19 Feature Extraction Based Classification Ensemble Method	Accuracy Average Precision Specificity Sensitivity	The ensemble model that has been suggested combines CNN with feature extraction-based techniques to enhance classification performance

Table 1: Continued

Zhang *et al*. (2020a)	DermIS Digital Database, Dermquest Database	WOA based CNN	Sensitivity Specificity PPV NPV Accuracy	70% of the data came from the training set, while 10% came from the validation set. Test sets were made using the remaining 20% of the material. Compared to the other ten approaches, the CNN/WOA method is the most accurate. This is caused by the merger of the CNN with the whale optimisation algorithm. When the CNN is subjected to this optimisation strategy, it is able to avoid the local minima. This results in a global minimum for the BP problem in the CNN and enhances the effectiveness of the suggested approach
Senan and Jadhav (2021)	PH2 Database	Feature Extraction using ABCD Rule - Extracting features is used by means of ABCD rule	Specificity Sensitivty Accuracy	The diagnosis of the images followed the accepted procedures. TDS is 5.65 in the proposed system. The exceptional resolution of the pictures allowed for an 84% accurate diagnosis
Garcia (2021)	ISIC 2019 PH2 Database 7 Point Criteria Evaluation Database	ResNet50 Model - 50 convolutional layers	-	The model's generalisation on the target dataset was enhanced, and the model's ability to identify the melanoma class was increased, according to the meta-learning experiment findings.
Khamparia *et al*. (2021)	International Skin Imaging Collaboration (ISIC) image archive	Transfer Learning	Precision Recall F1-score Accuracy	Based on the results, it is reasonable to draw the conclusion that the proposed framework performs skin lesion categorization more accurately than earlier pretrained deep learning architectures
Arif *et al*. (2022)	Interactive Atlas of dermoscopy (EDRA), International Skin Imaging Collaboration (ISIC)	K-means CNN R-CNN	Accuracy Precision	The modified K-means clustering performs group image segmentation better than existing techniques. The classification component receives these grouped photographs and categorises them as benign and malignant melanoma lesions
Sreelatha *et al*. (2019)	PH2 dataset	GFAC model	Accuracy Precision	The proposed image segmentation technique has a Disc Similarity Coefficient of 97.08, which is quite high in comparison to any other current technique
Raza *et al*. (2022)	Acral Melanoma and Benign Data Set	VGG16 Xception InceptionResnetV2 DenseNet121 DenseNet169 DenseNet210	Accuracy Precision Recall F1 score Sensitivity, Specificity	On the acral melanoma dataset, the ensemble-based method greatly beat all four individual models in terms of accuracy. Dermoscopy images of benign nevi and acral melanoma were categorised with 97.83% sensitivity, 97.50% specificity, and 97.93% accuracy using the suggested model
Hasan *et al*. (2019)	ISIC Dermascopic Archive Database	Basic CNN aglorithm	Recall Specificity F Measure Precision	The experimental and evaluation part suggests that the model can be utilised as a starting point for assisting medical professionals in detecting skin cancer. By gathering a few random images, any doctor can get accurate results, but the traditional method takes too long to accurately identify cases
Zhang *et al*. (2020b)	Dermquest DermIS Digital Database	Optimized CNN	Accuracy Sensitivity	The efficiency result for CNN was optimised using an upgraded version of the whale optimisation technique. To reduce the error between the network's output and the desired output, the optimum weights and biases in the network are discovered using the optimisation technique. Results demonstrated that the suggested strategy provides the best success for skin cancer diagnosis
Wen *et al*. (2022)	ISIC Archive (various years)	Vision Transformers (ViTs), Hybrid CNN-Transformer models, Attention Mechanisms, Explainable AI (XAI) techniques (e.g., Grad-CAM)	Accuracy, Precision, Recall, F1-score, AUC, Explainability scores (e.g., localization accuracy)	Studies are increasingly exploring ViTs and hybrid architectures to capture global and local features more effectively. Attention mechanisms highlight crucial regions in the images, improving diagnostic accuracy and interpretability. XAI methods are being integrated to provide dermatologists with insights into the model's decision-making process, fostering trust and clinical adoption
Himel *et al*. (2024)	HAM10000, ISIC 2019	Lightweight CNN architectures (e.g., MobileNetV3, EfficientNet), Spiking Neural Networks (SNNs), Meta-learning	Accuracy, Sensitivity, Specificity, Computational Efficiency (FLOPs, inference time)	Research is focusing on developing more efficient and resource-friendly models for real-time or mobile applications. SNNs offer potential for low-power inference. Meta-learning techniques aim to improve generalization with limited data
Kassani and Kassani (2019)	ISIC dataset	ResNet50 AlexNet Xception VGGNet16 VGGNet19	Accuracy F-score	With a classification accuracy of 92.08 percent and an F-score of 92.74 percent, ResNet50 outperforms AlexNet, Xception, VGGNet16, and VGGNet19 architectures in testing

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Motivation

In the early 20th century, skin cancer detection was performed by diagnosing and identifying large macroscopic features and lesions on the skin. This was a very tedious process making it impossible for early detection of skin cancer. However, with time, technology evolved and techniques evolved for the better. Image processing is a vast area and covers a number of interesting and fascinating concepts under the field of visualisation in Computer Science. The main motive of this research is to contribute to the healthcare sector and medical fraternity by comparing the different available ML algorithms for image detection which would help in the early detection of skin cancer. Most of the research focuses on implementing and comparing two to three image detection algorithms for the diagnosis of skin cancer. However, in a fast-moving world, with technology advancing rapidly, it's essential to analyse and comprehend the best out of all the available algorithms. In order to draw comparisons and conclusions about one of the most accurate, efficient and precise algorithms, the authors of this paper have implemented and analysed various parameters of five different classification algorithms using a dermatologically attested dataset.

Dataset Selection and Visualisation

The proposed machine learning algorithms for the diagnosis of skin cancer were trained using the ISIC 2017 dataset. The dataset HAM10000 (Human against Machine with 10,000 training images) contains approximately 10015 photos of skin lesions was used to conduct the preliminary analysis. Figure 2 depicts how skin cancer affects people by taking age as an attribute. It was observed that skin cancer was most prevalent in 45-year-olds. Figure 3 depicts how skin cancer affects people by taking gender as an attribute. It was found to be more prevalent in men. Figure 4 portrays the age and gender of skin cancer patients. Figures 5 and 6 outline how skin cancer affects different locations in the body. Figure 7 depicts the seven most common types of skin cancer.

Analysis and Discussion of Algorithms

Decision Trees, Random Forests, Support Vector Classifier, Gradient Boost Method, and CNN are the methods that were used in this study. Although it can be used to address classification and regression problems, decision trees are most frequently utilised to address classification problems (Taha Jijo and Abdulazeez, 2021). Each leaf node in this tree-structured classifier corresponds to the classification outcome, while internal nodes indicate dataset attributes, branches correspond to decision rules. The supervised learning approach is used by the well-known machine learning algorithm Random Forest. Its foundation is ensemble learning, a method for combining several classifiers to take on a difficult task and enhance the performance of the model. Classification and regression issues can be solved using the Support Vector Machine, or SVM, a popular Supervised Learning technique. However, it is mostly utilised in Machine Learning to address categorization issues (Tschandl, 2018; Hu *et al*., 2018). One popular boosting technique is gradient boosting. Each prediction in gradient boosting corrects the error of its predecessor. The training instance weights are not changed, unlike Adaboost, and each predictor is trained using the predecessor's residual errors as labels. Convolutional Neural Networks (CNNs) are feed-forward neural networks that process data in a grid-like pattern to assess visual images. A ConvNet is another name for it. Using a convolutional neural network, items in a picture can be recognised and categorised (Andre *et al*., 2017; Zhen *et al*., 2019).

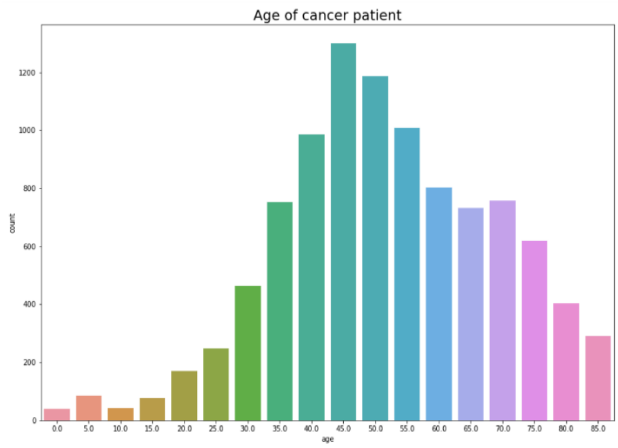

Fig. 2: It can be observed that skin cancer was most prevalent in 45-year-olds closely followed by 50-year-olds

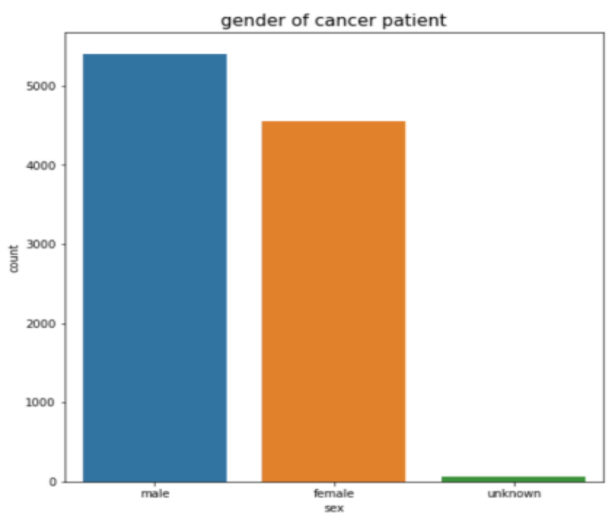

Fig. 3: Graph depicting number of cases with respect to gender. Skin cancer was found to be more prevalent in men

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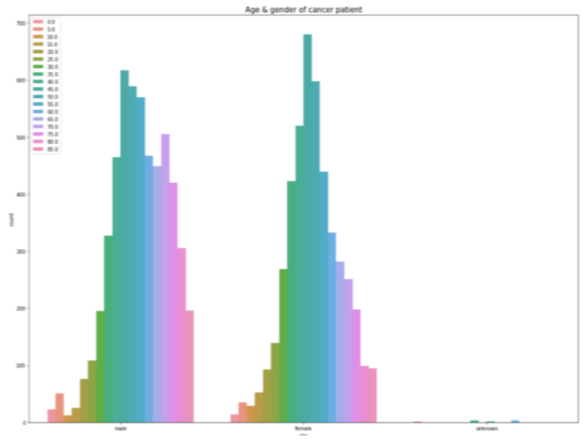

Fig. 4: Figure depicting the age and gender of cancer patients

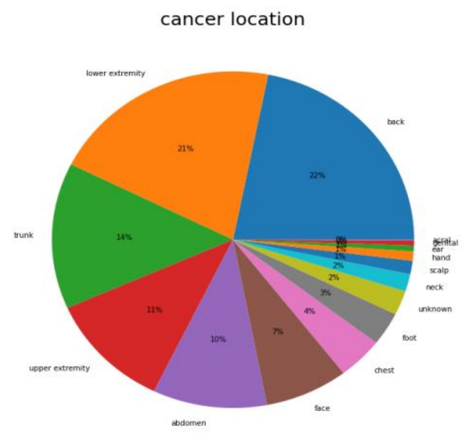

Fig. 5: Depiction of distribution of Cancer patients based on location

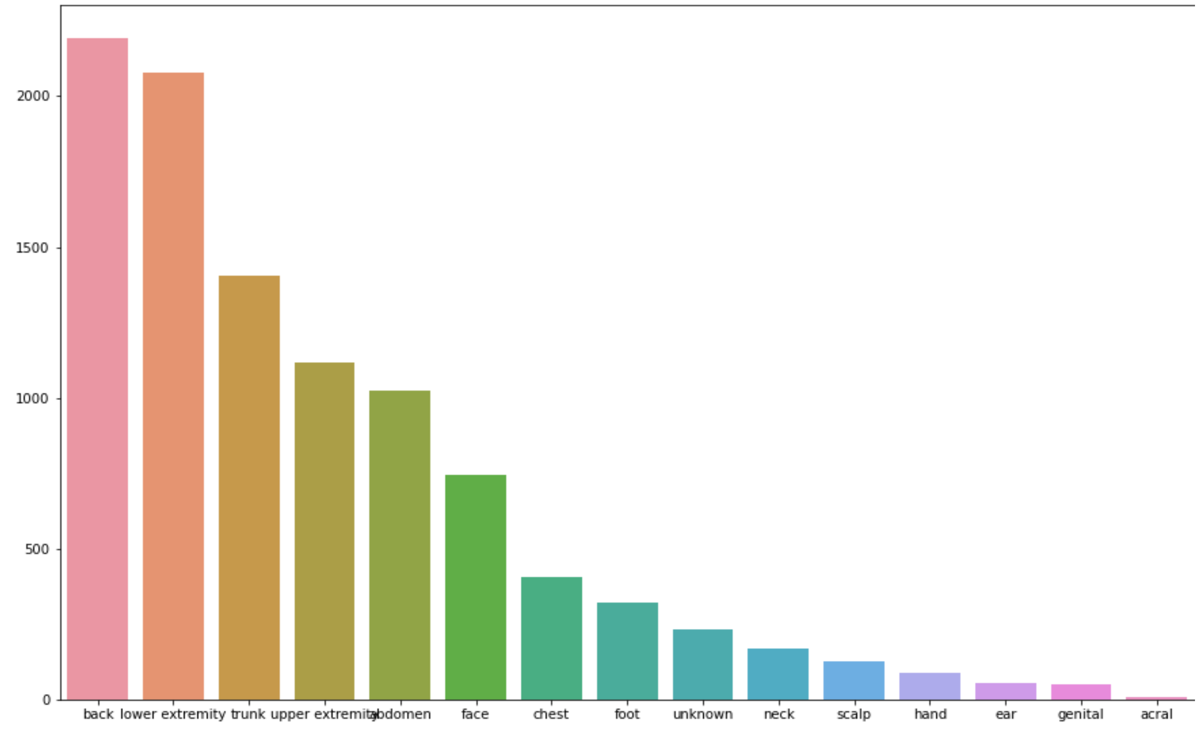

Fig. 6: Figure depicting the distribution of skin cancer location

Decision Trees

Decision trees are seemingly the best intuitive machine learning classification algorithms and give a good passage into the applied side of things with regards to image classification. Here in image classification, the DT's are easy to interpret and very reliable, since the "if-then" rule-based hierarchy is represented by a tree with leaves designating a class as benign or malignant and branches using logical conjunction to produce a value. As a result of these values, a set of guidelines for interpreting instances of a certain class are generated (Luo *et al*., 2021). One of the major advantages of DT's is that they are usually very fast to compute and there is no assumption about data distribution. Basically, the decision tree is just a set of decision rules which converts continuous data, like the spectral information from a skin image, into discrete skin cancer information, such as malignant or benign class (Lakshminarayanan *et al*., 2022). Each pixel will be assigned to a skin cancer class if its spectral information fits the conditions that are required according to DT. In DT we have different criteria which can be used to make the tree. In this paper, we have performed the DT for Gini Index and entropy on the skin cancer image dataset. The workflow of the decision tree algorithm is shown below in Figure 8.

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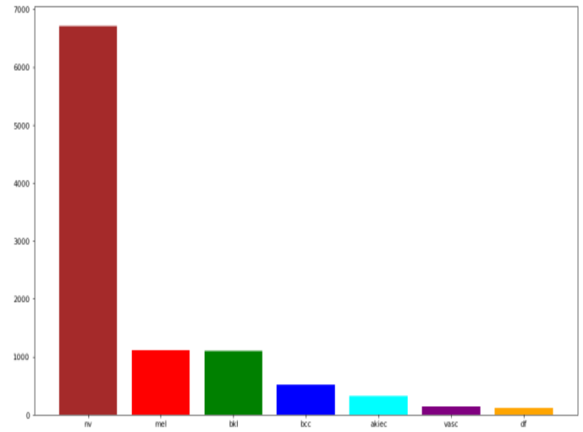

Fig. 7: Figure depicting the seven most common types of skin cancer. Neves was found to be the most common type of skin cancer

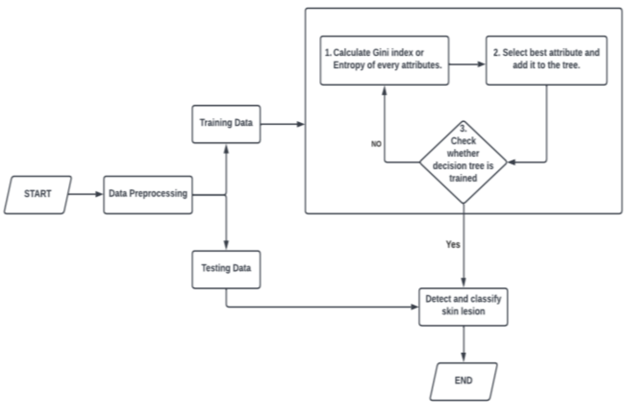

Fig. 8: Workflow diagram of decision tree algorithm

Random Forests

A technique for classification and regression called Random Forest (RF) uses supervised learning. Compared to other machine learning methods for image classification, random forests provide a number of advantages. It can use continuous and categorical data sets, is non-parametric, is simple to parameterize, is adept at handling outliers in training data, and is not very sensitive to over-fitting. An ensemble model called random forest is essentially a group of trees (Dandu *et al*., 2021). It is said that the more trees there are, the more robust a forest is. In the case of random forests, several decision trees are created on randomly selected data samples and the response is calculated based on the outcome of all of the decision trees. For finding the best outcome from the decision trees they perform voting (Ngan Thanh *et al*., 2021). In other words, if we have 1000 trees created on the skin cancer image dataset and among 1000, we have 800 which predict that a particular pixel is malignant and the rest 200 which predict benign (Murugan *et al*., 2021; Babu and Peter, 2021). So, the predicted output will be malignant as we can see that the majority predict malignant. The workflow of the Random Forest algorithm is shown below in Figure 9.

Support Vector Classifier

Support Vector Machine (SVM) and Support Vector Classifier (SVC) are basically the same if the hyper-plane that we are using for classification in SVM is in linear condition, then the condition is SVC (Babu and Peter, 2021; Balasubramaniam, 2021). The main objective of the SVC is to fit the training data which is provided and use it to return the best fit hyper-plane that divides the training data. After obtaining the hyper-plane we can then feed the testing dataset into the classifier to obtain output and find different performance measures like recall and precision (Ansari and Sarode, 2017; Balasubramaniam, 2021). It tries to find a Maximum Marginal Hyper-Plane (MMH) that best divides the dataset into classes i.e., malignant or benign. Some of the key parameters in SVC are Gamma, c, and kernel. Here the main hyper-parameter is kernel. It maps the observations into some feature space. Types of Kernels are Linear, Radial Basis Function (RBF), and Polynomial Kernel (poly). The choice of the kernel and their hyper-parameters greatly affect the separability of the classes and the performance of the algorithm (Hekler *et al*., 2019; Han and Zheng, 2020). C parameter adds a penalty for each misclassified data point. It is directly proportional to the distance to the decision boundary. Gamma parameter controls the distance of influence of a single training point. The workflow of the SVC algorithm is shown below in Figure 10.

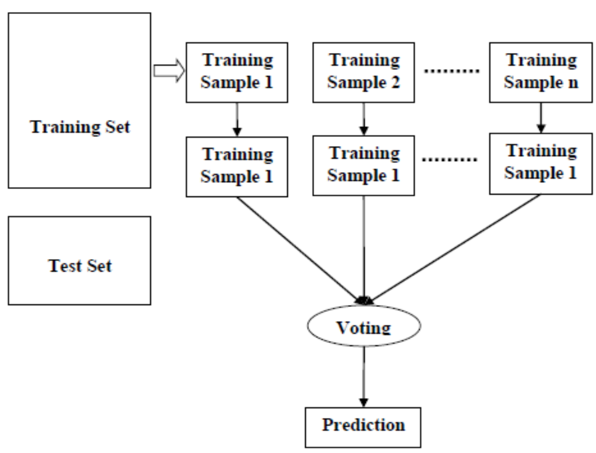

Fig. 9: Workflow diagram of random forest algorithm

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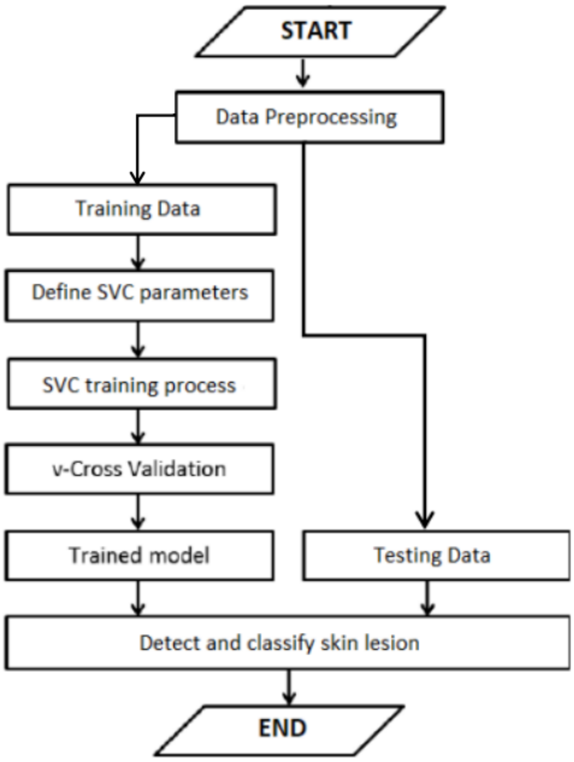

Fig. 10: Workflow diagram of SVC algorithm

Gradient Boost Method

Gradient Boost Method (GBM) is one of the ML algorithms used for classification and regression. It is one of the ensemble techniques used for the purpose of classification and has been quite popular because of its ease of use and flexibility. The main essence of this algorithm is the fact that weak learners can be boosted to become better at the training and learning phase (Tschandl *et al*., 2019). One of the first boosting algorithms was AdaBoost which was later modified and improvised with by various scientists and researchers for further developments. This technique focuses on the two or more derivatives of the same function being used and is an interactive functional gradient algorithm that aims to reduce the loss of the function by selecting one which possesses a negative gradient or a weak hypothesis (Alkhushayni *et al*., 2022; Brinker *et al*., 2018). The three main components of this algorithm are - loss function, weak learner, and the additive model. With regards to the image dataset used for this research, the algorithm works by adding trees repeatedly by splitting and dividing the characteristics. With every new iteration, the new set of rules are merged and this decreases the loss function (Javaid *et al*., 2020). Usually, the second order derivative is utilised for achieving the loss function. The diagram given in Figure 11 elaborates on the workflow of this algorithm.

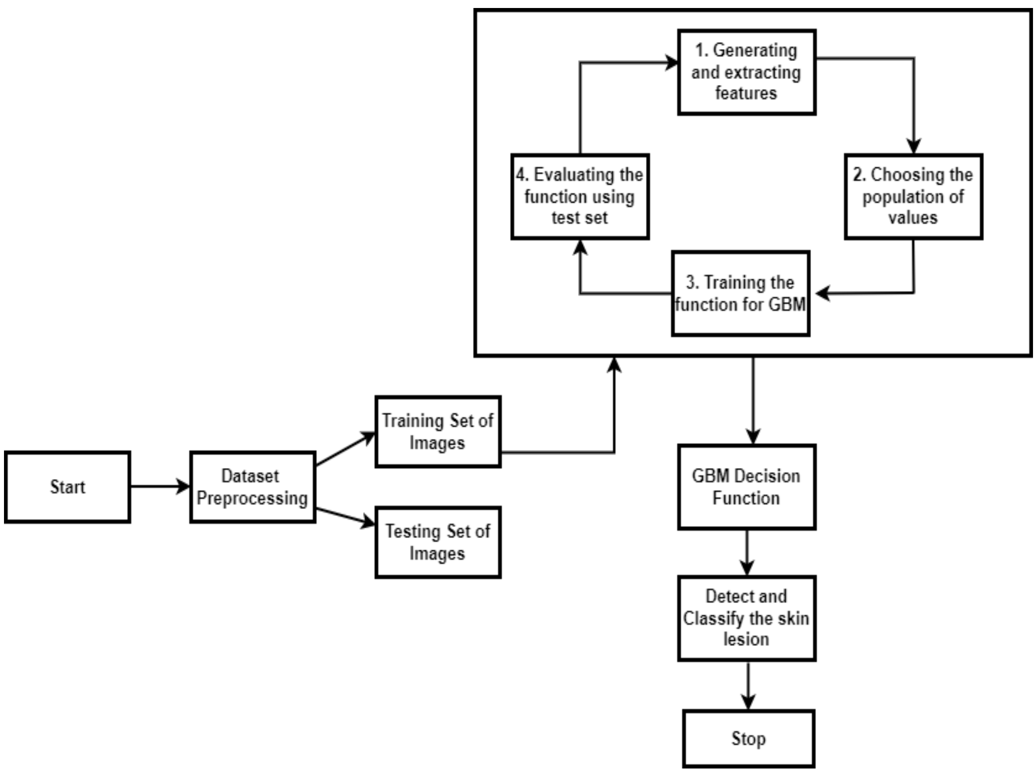

Fig. 11: Workflow diagram of GBM algorithm

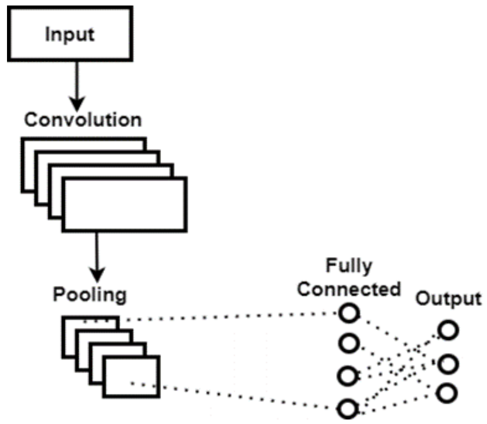

Fig. 12: Workflow diagram of CNN algorithm

Convolutional Neural Network (CNN)

The CNN algorithm contributes to the uniqueness of CNN when compared to most of the ML algorithms as it focuses on processing information and data the same way that the human brain does (Rezaoana *et al*., 2020). This algorithm revolves around the feature extraction technique wherein suitable characteristics are extracted from the image based on which certain patterns are drawn. Convolution, in image processing, literally translates to the use of point-based multiplication between functions where one function represents the image pixel matrix and the other represents the filter being used (Malladi *et al*., 2021). In this algorithm, there are many convolutional layers which extract features from the images in the dataset which are finally utilised for acquiring the required output. The main steps involved in CNN for the classification and detection of cancerous skin lesions include preparing the image dataset of ISIC skin cancer for training. Following this, the data is then split into training and test data using the 80-20 rule. Labels and features are assigned using the neural networks. The CNN model is then trained and compiled for around twenty to thirty epochs or until a good accuracy is achieved (Sedigh *et al*., 2019). The score and accuracy of the model is then computed and the model is validated using test images. The workflow of the diagram is given as shown in Figure 12.

Results

In this paper, we have used CNN with the help of Keras and TensorFlow in python, for training our model for skin cancer detection. We have compared these models with the help of performance measures like accuracy, precision, recall, and F1 score as shown in Table 2.

First, we have performed image pre-processing to improve the quality of the image so that the model can be better analysed. So, the images are resized and segmented using Image Thresholding Techniques. Our evaluation encompassed classical machine learning algorithms alongside CNN. Using the scikit-learn library, we instantiated Decision Tree Models with both Gini index and Entropy criteria, a Random Forest Model, an SVM model, and a Gradient Boosting Machine (GBM) model, calculating their respective performance metrics. As indicated in Table T1, the Decision Tree model yielded accuracies of 66 and 70% for Gini Index and Entropy, respectively, while the Random Forest model achieved 79% accuracy. Surprisingly, our CNN implementation, comprising six layers, yielded an accuracy of 80.5% on the testing dataset, slightly lower than the SVM model. However, a deeper examination revealed that the SVC model exhibited a recall score of 0, suggesting it incorrectly classified all testing images as benign. This highlights a limitation of the SVC model in handling class imbalance. Going ahead, our findings raise important questions about why CNNs could be superior to conventional machine learning models in the detection of skin cancer. More research is necessary to determine if CNNs are inherently able to identify minute characteristics that are suggestive of skin cancer pathology that other models could miss. This investigation is crucial to expanding our knowledge of CNNs' applications in medical image processing and their possible influence on raising skin cancer diagnosis accuracy.

Table 2: Performance metrics of different algorithms

Model		Class	Accuracy	Precision	Recall	F1 score
Decision tree	Gini Index	Benign	0.66	0.81	0.75	0.78
		Malignant		0.21	0.26	0.23
	Entropy	Benign	0.7	0.82	0.81	0.81
		Malignant		0.25	0.26	0.26
Random forest		Benign	0.79	0.81	0.96	0.88
		Malignant		0.32	0.08	0.12
SVC		Benign	0.81	0.81	1	0.89
		Malignant		0	0	0
GBM		Benign	0.75	0.82	0.88	0.85
		Malignant		0.31	0.21	0.25
CNN			0.805	0.78	0.8	0.79

Conclusion

We can infer that the categorization accuracy is a poor metric to use with this dataset due to class imbalance. Here we are more concerned about not allowing our predictions to have any false negatives, the correct metric which should be used here should be recall. The recall of the SVC model is 0 since it declared all the testing images benign. Hence, SVC is a very poor model. While the CNN model, on the other hand, has a good recall of 0.8. Thus, the CNN model is reasonably good. Hence, we can conclude that the CNN model works better than classical Machine learning algorithms for the detection of Melanoma in Skin Lesions.

Future Scope

Considering the endless possibilities of algorithms and techniques which can be reinvented for increased accuracy and efficiency in the models being curated, skin cancer detection is surely an area offering extensive research scope. Skin cancer is one of the most prevalent types of cancer across the globe and its early diagnosis can help save millions of lives of people. The techniques and ML algorithms elaborated and implemented in this paper focuses on the models and software side of diagnosis (Adegun and Viriri, 2021; Kaur *et al*., 2021). There are many techniques and strategies which can be further researched upon which revolve around the use of sensory equipment and tools to detect and diagnose skin cancer and lesions. With respect to the CNN models, different types of architectures of neural networks can be further researched upon including those of AlexNet, ResNet, ImageNet, etc. to compare and contrast the accuracy and precision of classification and detection results obtained from each of them (Saba, 2021; Vinod and Thomas, 2021;). Furthermore, models which can assess and detect cancer based on text-based attribute dataset can also be extended to make skin cancer detection and early diagnosis a versatile and flexible domain.

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Author’s Contributions

All authors equally contributed in this work.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

Conflict of Interest

The authors declare that no conflict of interest regarding publication of this work.

Data Availability

'Data sharing’ is applicable to this article, is already available online at UCI repository.

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