Skin Lesions Classification: A Comparative Analysis of SGD and SVC for Optimal Accuracy

El-Sayed M. El-kenawy, Marwa M. Eid, Manish Kumar Singla, Doaa Sami Khafaga, Amel Ali Alhussan, and Amal H. Alharbi

Delta Higher Institute of Engineering and Technology, Mansoura 35511, Egypt; Applied Science Research Center, Applied Science Private University, Amman, Jordan; Faculty of Artificial Intelligence, Delta University for Science & Technology, Mansoura 35111, Egypt; Jadara University Research Center, Jadara University, Jordan; Department of Biosciences, Saveetha School of Engineering, SIMATS, Chennai, India; Department of Computer Sciences, Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia

Abstract. In the ever-evolving area of Machine Learning, choosing the proper classifier to get the maximum accuracy is one of the most critical yet very competitive prerequisites, which are always more sensitive when even slight variations in accuracy are possible to make a huge difference. This study addresses this problem by conducting a comparative analysis of two widely used classifiers: the Stochastic Gradient Descent Classifier (SGDC) and the Support Vector Classifier (SVC). To maximize accuracy, we tested each algorithm on a classification task, repeating the experiment several times. The accuracy yielded was significantly higher for SGDC in the aggregate, yielding an absolute accuracy of 97.5%, while SVC yields an absolute accuracy of only 82.3%. The performance difference of 15.2% compared with SGDC illustrates the appropriateness of the method for highly accurate applications. This study delivers practical implications regarding specific performance G-means, which recognize the most effective classifier in a particular project and stimulate further investigation to enhance the comparison scope concerning various algorithms and data sets.

Keywords. Machine Learning, Classification, Accuracy, SGDC, SVC, Classifier Comparison, Objective Function.

1. INTRODUCTION

The use of machine learning in dermatology has accelerated in parallel with the global rise in skin cancer incidence and the persistent shortage of specialist dermatologists, creating a clear demand for scalable, accurate, and automated diagnostic support systems. In contemporary clinical workflows, these systems typically analyze dermoscopic or clinical photographs to assist clinicians in differentiating benign from malignant lesions, thereby improving triage, prioritizing biopsy decisions, and potentially shortening time to treatment. Beyond simple pattern recognition, modern pipelines incorporate standardized image acquisition, quality control, and metadata handling to mitigate variability introduced by devices, lighting, and skin phototypes.

Concurrently, evidence indicates that a spectrum of AI approaches—from classical machine learning to deep convolutional architectures—can materially improve lesion classification performance when trained on sufficiently large, well-annotated datasets. CNN-based models leverage hierarchical feature learning to capture clinically salient patterns (e.g., asymmetry, border irregularity, color variegation, dermoscopic structures) and have approached dermatologist-level accuracy in specific benchmarks. Nevertheless, persistent challenges remain, including class imbalance, domain shift across institutions and imaging devices, and the need for interpretable outputs that align with clinical reasoning. Current research therefore emphasizes stronger dataset curation, stratified evaluation, and the fusion of segmentation, feature extraction, and classification modules to support reliable deployment in heterogeneous real-world settings.

Machine learning has also seen numerous studies evaluating whether traditional classifiers or deep networks perform better in identifying skin lesions. Researchers have investigated standard classifiers, such as the Stochastic Gradient Descent Classifier (SGDC) and Support Vector Classifier (SVC), to assess their diagnostic reliability. Findings demonstrate that classifier choice significantly affects diagnostic performance in terms of accuracy, sensitivity, and specificity. Furthermore, the automatic detection of complex structures in medical images has been made possible through convolutional neural networks (CNNs).

2. LITERATURE REVIEW

Artificial intelligence has found potential use in dermatology, especially in the detection of skin cancer. Advances demonstrated in recent research show that machine learning (ML) and deep learning (DL) models can provide improved diagnostic predictions by studying datasets and can help in early disease detection and treatment. Specific research areas aim to improve algorithms for diagnosing and grading skin lesions to address the shortage of dermatologists and the rising prevalence of skin disorders.

As reported in recent studies [1], machine learning (ML) employs statistical models and algorithms that learn incrementally from data to predict future outcomes. Deep convolutional neural networks (CNNs) are now trained to assess skin images for cancer. Although specialists are efficient in diagnosing skin cancer, the growing demand for diagnostic accuracy has increased the need for automated systems that can assist dermatologists, improve efficiency, and reduce patient costs.

Skin diseases account for nearly 1.79% of the global burden of disease. According to recent findings [2], a Multi-Class Multi-Level model based on a divide-and-conquer strategy was proposed to classify multiple skin diseases. The model, evaluated on 3672 images from multiple sources, achieved a diagnostic accuracy of 96.47%, outperforming prior Multi-Class Single-Level models. A novel approach for skin cancer identification using hybrid features [3] employs a k-nearest neighbor (kNN) algorithm with 5-fold cross-validation. The surface fractal dimension is calculated using a 2D generalization of Higuchi's method. Tested on 7-Point, Med-Node, and PH2 datasets, the model achieved accuracies of 95.42%, 94.71%, and 94.88%, respectively.

As highlighted in [4], an approach for automatic lesion detection integrates features from photometric and spatial domains using the AlexNet architecture combined with a local optimal-oriented pattern, achieving 94.7% accuracy on the PADUFES-20 and MED-NODE datasets. A decision-making system [5] integrates multiple classifiers including neural networks using weighted voting, with fine-tuned CNNs (GoogleNet, ResNet-101, NasNet-Large) fused with a Support Vector Machine classifier, yielding superior diagnostic performance. In [6], a deep CNN system trained on 38,283 dermal images achieved over 90.3% sensitivity and 89.9% specificity. Recent studies [7] demonstrated that a proposed model predicted clinical management choices directly from images, improving accuracy by 13.73% and reducing over-diagnosis cases by 24.56%.

A study [8] proposed deep learning frameworks using fully convolutional residual networks (FCRN) combined with a lesion index calculation unit (LICU), achieving segmentation, feature extraction, and classification accuracies of 0.753, 0.848, and 0.912 on the ISIC 2017 dataset. For melanoma detection [9], fine-tuned transfer learning models (ResNet50, InceptionV3, Inception-ResNet) on ISIC 2018 achieved accuracies of 83.7%, 85.8%, and 84%. Hybrid metaheuristics such as BA-ABC [10] enhance image quality by optimizing contrast and brightness, achieving a Dice coefficient of 94.6% on ISIC 2016–2018 datasets. Recent advancements in optimization and ML have significantly improved classification accuracy [11], with metaheuristic methods showing promise in feature selection and dimensionality reduction [12][13][14][15].

3. Discussion and Results

The following section provides a critical review of the dataset, data analysis, and the performance of machine learning models in the classification of skin lesions. Skin lesions, especially those presented in the ISIC 2019 dataset due to the rich variety of them, can be effectively utilized for training and evaluating classification models. The use of two models, SGDClassifier and SVC, involves a comparison regarding the ability of each model to correctly diagnose skin lesions.

3.1. Dataset

The dataset used in this study is the*ISIC 2019* dataset, which contains image data for skin lesion classification. The dataset consists of 25,331 dermoscopic images contributed from previous ISIC challenges (2018 and 2017). It encompasses nine diagnostic categories: melanoma, melanocytic nevus, basal cell carcinoma, actinic keratosis, benign keratosis (including solar lentigo, seborrheic keratosis, and lichen planus-like keratosis), dermatofibroma, vascular lesion, squamous cell carcinoma, and “none of the above.” This diverse collection provides a rich and heterogeneous data source useful for training and evaluating machine learning models. The dataset is publicly accessible on Kaggle at: https://www.kaggle.com/datasets/andrewmvd/isic-2019

3.2. Data Analysis

Figure 1 is a bar diagram which represents the distribution of various classifications of melanoma in the given dataset. This helps to understand how frequently each of the skin lesion categories occur, and to see how common each type of skin lesion is.

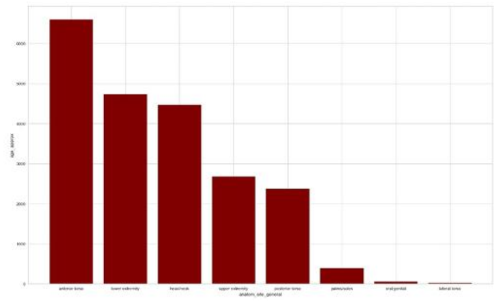

Fig. 1. Bar Plot for Melanoma Classification Dataset

3.3. Machine Learning Results

Table I displays the accuracy of two predictive models, SGDClassifier and SVC, in identifying melanomas. This table includes accuracy, sensitivity (TRP), FScore, specificity

(TNP), PPV, and NPV. As clearly shown in the table, the SGDClassifier yields reasonable performance in most aspects such as achieving an accuracy of 0.968 and specificity that is almost 1.000. On the other hand, the SVC model tends to have much lower values of all these features, with accuracy of 0.824 and specificity of 0.812, meaning that SGDClassifier is more efficient at this particular type of classification.

TABLE I. Performance Comparison Between SGD Classifier and SVC

Model	Accuracy	Sensitivity	F-Score	Specificity
SGD Classifier	0.968	0.942829	0.934569	0.998787
SVC	0.82381	0.833113	0.799205	0.812449

Figure 2 presents the confusion matrices for all models in the form of a heatmap, which enhances the visualization of the differences in both accuracy and sensitivity. The heatmap shows that all the models have a reasonably good attitude towards accuracy with a lower sensitivity towards SVC. Altogether, the results of this study stress the possibility of using classifiers within the machine learning framework.

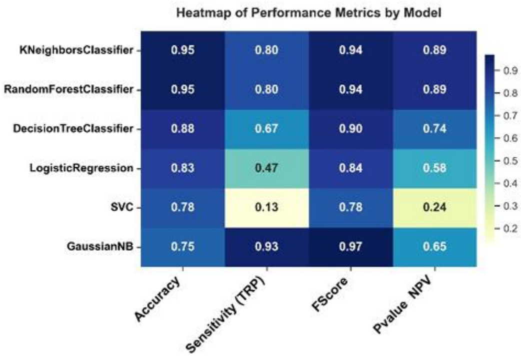

Fig. 2. Heatmap of Performance Metrics by Model

4. CONCLUSION

The comparative analysis between the Stochastic Gradient Descent Classifier (SGDC) and the Support Vector Classifier (SVC) highlights a significant performance disparity in the context of skin lesion classification. Specifically, SGDC achieved a mean accuracy of 97.5%, surpassing SVC's 82.3% by approximately 15.2%. This considerable difference in performance underscores the SGDC model's superior capability in handling high-dimensional feature spaces and large-scale datasets efficiently. The finding also illustrates that stochastic optimization and adaptive learning strategies can enhance convergence speed and model generalization in medical imaging tasks where feature distributions are highly nonlinear and heterogeneous.

Beyond the numerical superiority of SGDC, the results point to a broader insight: theoretical advantages of certain algorithms, such as SVC's robustness in smaller or linearly separable datasets, do not necessarily translate into improved real-world performance. Factors such as dataset complexity, image noise, feature scaling, and hyperparameter sensitivity often influence classifier effectiveness in practice. Hence, model selection should not rely solely on theoretical assumptions but must be grounded in empirical evaluation across domain-specific datasets.

5. References

[1] K. Das, C. J. Cockerell, A. Patil, P. Pietkiewicz, M. Giulini, et al. Machine learning and its application in skin cancer. International Journal of Environmental Research and Public Health, 18(24), 2021.

[2] N. Hameed, A. M. Shabut, M. K. Ghosh, and M. A. Hossain. Multi-class multi-level classification algorithm for skin lesions classification using machine learning techniques. Expert Systems with Applications, 141:112961, 2020.

[3] S. Moldovanu, F. A. Damian Michis, K. C. Biswas, A. Culea-Florescu, and L. Moraru. Skin lesion classification based on surface fractal dimensions and statistical color cluster features using an ensemble of machine learning techniques. Cancers, 13(21), 2021.

[4] J. Alyami, A. Rehman, T. Sadad, M. Alruwaythi, T. Saba, et al. Automatic skin lesions detection from images through microscopic hybrid features set and machine learning classifiers. Microscopy Research and Technique, 85(11):3600–3607, 2022.

[5] H. El-Khatib, D. Popescu, and L. Ichim. Deep learning–based methods for automatic diagnosis of skin lesions. Sensors, 20(6), 2020.

[6] L. R. Soenksen, T. Kassis, S. T. Conover, et al. Using deep learning for dermatologist-level detection of suspicious pigmented skin lesions from wide-field images. Science Translational Medicine, 13(581):eabb3652, 2021.

[7] K. Abhishek, J. Kawahara, and G. Hamarneh. Predicting the clinical management of skin lesions using deep learning. Scientific Reports, 11(1):7769, 2021.

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

[9] W. Gouda, N. U. Sama, G. Al-Waakid, M. Humayun, and N. Z. Jhanjhi. Detection of skin cancer based on skin lesion images using deep learning. Healthcare, 10(7), 2022.

[10] S. Malik, T. Akram, M. Awais, M. A. Khan, M. Hadjouni, et al. An improved skin lesion boundary estimation for enhanced-intensity images using hybrid metaheuristics. Diagnostics, 13(7), 2023.

[11] El-Sayed M El-Kenawy et al. Smart city electricity load forecasting using greylag goose optimization-enhanced time series analysis. Arabian Journal for Science and Engineering, 2025.

[12] El-Sayed M Elkenawy et al. Greylag goose optimization and multilayer perceptron for enhancing lung cancer classification. Scientific Reports, 14(1):23784, 2024.

[13] Ahmed El-Sayed Saqr, Mohamed S Saraya, and El-Sayed M El-Kenawy. Enhancing co2 emissions prediction for electric vehicles using greylag goose optimization and machine learning. Scientific Reports, 15(1):16612, 2025.

[14] El-Sayed M Elkenawy, Amel Ali Alhussan, Marwa M Eid, and Abdelhameed Ibrahim. Rainfall classification and forecasting based on a novel voting adaptive dynamic optimization algorithm. Frontiers in Environmental Science, 12:1417664, 2024.

[15] Amel Ali Alhussan, El-Sayed M. El-kenawy, Doaa Sami Khafaga, Amal H. Alharbi, and Marwa M. Eid. Groundwater resource prediction and management using comment feedback optimization algorithm for deep learning. IEEE Access, 2025.