International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Melanoma Stage Classification Based on Hybrid Heterogeneous Multi-Classifier Ensemble Learning

Shweta M.[1], Vishwanath Burkpalli[2]

Submitted: 28/05/2023 **Revised**: 13/07/2023 **Accepted**: 29/07/2023

Abstract: Background: Melanoma is one of the most dangerous types of skin cancer, and it can be fatal if it is not detected at initial stage. Therefore, melanoma detection requires a precise diagnosis.

Objective: To build Hybrid Heterogeneous Multi-Classifier Ensemble learning models to classify and identify skin cancer.

Methods: Models that help make skin cancer predictions more accurate are built using a model-driven framework in the cloud that uses machine learning (ML) methods at its core. The study shows how to make models and use them to put skin tumors into groups.

Results: Hybrid Heterogeneous Multi-Classifier Ensemble Learning models built here are tested on ISIC2019 dataset, and accuracy of 95.10% was observed.

Conclusions: A practitioner may easily construct the hybrid ensemble machine learning models to predict skin cancer using the model-driven architecture. The suggested model can also find photographs that don't fit into any of the three classifications.

Keywords: *melanoma detection, skin cancer, machine learning, multiclass classifier, ensemble learning.*

1. Introduction

Cancer disorders are now among the most serious illnesses that endanger human life. Melanoma skin cancer is serious malignancies, may be fatal if not caught initially. Early detection of melanoma skin cancer lowers death rates and eases treatment-related problems. Skin cancer is an invasive condition brought on by body’s melanocyte cells, which develop abnormally and have a propensity to multiply and migrate via lymph nodes to harm neighboring tissues [1]. Injured skin cells produce a mole on surface of skin that may be classified as malignant or not, however melanoma is classified as cancer since it is serious and potentially fatal. Systems that automatically use computers to classify skin lesions accurately may help save lives.

Procedures utilized by doctors to assess and analyze melanoma scans are time-consuming, difficult to perform objectively, and prone to mistakes. This is mostly due to the complexity of skin lesion imaging. For the purpose of evaluating and being aware of skin lesions, image analysis requires the precise identification of lesion pixels. A substantial advancement in computer-aided diagnosis and prediction systems for skin cancer detection has been made thanks to the use of ML techniques in computer vision [2].

There has been substantial study into building computer image analysis algorithms in attempt to detect skin cancer quickly and at the early stage and address some of the issues stated above. To reduce needless biopsies while diagnosing melanoma, a number of non-invasive techniques have been suggested. Segmentation, features extraction, and classification make up the bulk of most techniques [3].

The melanoma patient's stage is crucial for the diagnosis of the disease. Cancer stage or tumor thickness are the key factors that influence cancer diagnosis during surgical therapy. The patient's tumor's size and stage are important diagnostic factors. Melanoma skin cancer stages: By doing a pathological examination, the tumor's thickness and depth are measured using the Breslow indexing and Clark scale. Only after conducting incisional or excisional surgery on a doubt lesion are these techniques appropriate for use.

[1]Dept of ISE, PDA College of Engineering, Kalaburagi, shwetamadiwal3@gmail.com,
[2]HOD and Professor, Dept of ISE, PDA College of Engineering, Kalaburagi, Vishwacmd@gmail.com

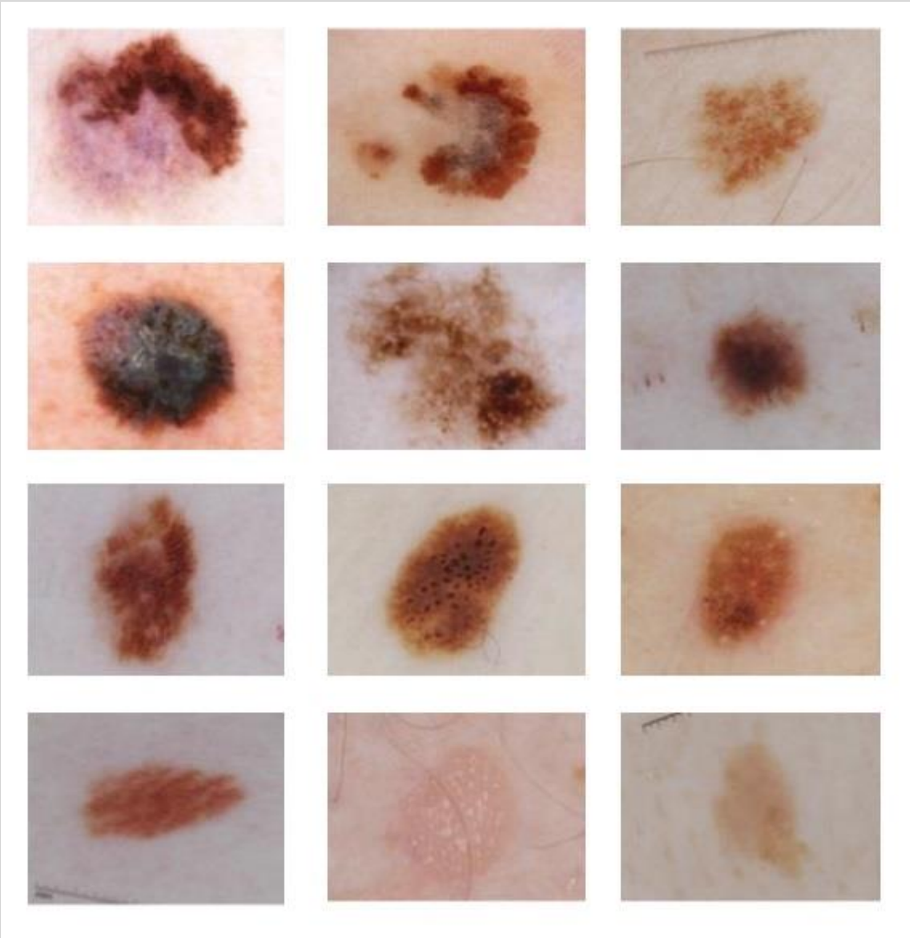

Fig. 1 ISIC dataset images.

Malenoma Staging

Initial clinical evaluation and histology confirmation determine the correct stage of melanoma. Use of the TNM method by American Joint Committee on Cancer results in clinical and pathologic stage assignments [4]. When index lesion has been histologically determined to be melanoma, other factors that affect the tumor's stage, or T, include ulceration, overall tumor thickness, and presence of mitosis in lesions with a thickness of less than 1 mm (T1) [5]. In our work we consider only 3 stages of malenoma for multiclass classification which are Stage 0, Stage 1 and Stage 2.

Goal of this study is to offer an updated ensemble machine learning-based algorithm to identify the stages of skin cancer and to validate the approach using the Skin Cancer ISIC2019 dataset [6]. There have been two suggested classification schemes, both of which use the Hybrid Ensemble Classifier algorithm and ML. The stages of melanoma skin cancer are divided into following categories based on thickness: Based on the thickness, the stages of melanoma skin cancer are identified. Stages 1 and 2 of melanoma are classified in the first suggested approach (binary classifier). This divides melanoma into two categories: first-stage tumor thickness 0.8 mm and second-stage tumor thickness > 0.8 mm. The second suggested approach divides the phases into three categories: tumor thickness 0.8 mm, tumor thickness > 0.8 mm to tumor thickness 2 mm, and tumor thickness > 2 mm. In order to demonstrate the superiority of the suggested technique, the performance of the proposed Hybrid Heterogeneous Multi-Classifier Ensemble Learning architecture is compared with other well-known machine learning models, including SVM, KNN, and NB. Innovative aspect of the work that is being given is the automated diagnostic approach for skin cancer categorization that is based on a new Hybrid Ensemble ML model configuration. In the comparative studies, the recommended model was assessed using a wide range of indicators. The F1-score, area under AUC curve, and accuracy and recall measurements were some of these indicators. The results demonstrate more accuracy in comparison to the initial ensemble and machine learning model.

This work makes the following contributions:

- By constructing numerous linked algorithms, a novel architecture of the H2MCEL model is provided for identifying skin lesions as malenoma stage 0, stage 1, and stage 2.
- Demonstrated effectiveness of proposed method on a real-world dataset of melanoma images, achieving

high classification accuracy and outperforming existing methods.

- Introduced feature selection strategy to optimize feature space and enhance the predictive power of the classifiers in the ensemble.
- Evaluated proposed system using rigorous experimental protocols, including cross-validation and comparison with other ensemble and single classifier approaches, to show robustness and generalizability of proposed system.
- On ISIC datasets, the suggested model does better than current cutting-edge techniques while using fewer filters and learnable parameters. So, it is a simple network for putting a large number of skin cancer cases into groups.

This paper is set up like this: Section 1 is an introduction, Section 2 is survey of related work, Section 3 is a description of the proposed system implementation, Section 4 is a look at the results, and Section 5 is a summary.

2. Literature Survey

Image-based skin cancer diagnosis has come a long way since it was first studied. Several ways have been tried. The International Skin Imaging Collaboration (ISIC) [6] event in 2018 became standard for spotting skin cancer because it included a challenge game. Researchers have tried a number of different sorting systems and methods to improve the accuracy of identification.

Feature Extraction Techniques

Rahman et al. [8] propose a hybrid feature fusion method for melanoma skin cancer detection, combining handcrafted features and deep learning (DL) based features. They extract handcrafted features like color, shape, texture, and use a pre-trained deep convolutional neural network (CNN) to obtain high-level features. These features are then concatenated and dimensionality reduction techniques are applied. Support vector machines (SVM) are used for classification, outperforming other classifiers. The proposed method demonstrates improved classification accuracy compared to existing approaches, highlighting effectiveness of hybrid feature fusion strategy.

The model put out by Giotis et al. [9] uses color and texture cues to categorize the pictures into benign and malignant. They employed Gaussian noise in pre-processing, the k-means technique for segmentation, the extraction of color and texture characteristics, and finally Cluster-based Adaptive Metric (CLAM) classifier for picture classification as a final step. The Med-node dataset showed an accuracy of 81% for this model.

Wahba et al. [10] propose a novel skin lesion classification method that combines empirical mode decomposition (EMD) and texture features with a quadratic SVM. The authors use EMD to decompose dermoscopic images into intrinsic mode functions (IMFs) and extract texture features, specifically gray level co-occurrence matrix (GLCM) and gray level run-length matrix (GLRLM). Study demonstrates that proposed method achieves a classification accuracy of 96.5%, outperforming other techniques, including other SVM kernels, artificial neural networks (ANN), and decision trees.

Machine Learning Models

A method of diagnosis was put out by Razmjooy et al. [11] to identify skin cancer that was malignant. By using edge detection and smoothing, they first got rid of superfluous scales. The approach then divided the area of interest into segments. Mathematical morphology eliminated the extra information. The authors of the research utilized an ANN that has been tuned to diagnose skin cancer. The Australian Cancer Database (ACD) was simulated, and the findings showed recommended strategy changed the way the procedure functioned. The technique uses the ANN approach, which is outdated and less accurate now.

Vocaturo et al. [12] used the Multi-instance learning (MIL) method to figure out that dysplastic nevi were caused by melanoma. Simulation results show that the MIL method could be used as one of the right tools for detecting skin cancer. MIL, on the other hand, was a simple poorly guided classification method based on sets that might give worse results in some situations. Dey et al. [13] suggested the best machine vision method for melanoma diagnosis. The diagnosing system's accuracy was increased using the Bat algorithm. The melanoma was effectively segmented using distance-regularized level-set (DRLS) segmentation approach. Correctness of the strategy was then shown by analyzing the major image performance metrics (IPM) on PH2 database.

Patil R. et al. [14] present a comprehensive review of ML techniques for melanoma cancer stage detection. Authors cover various algorithms, such as SVM, decision trees, and CNNs, while emphasizing the importance of feature extraction, selection, and data pre-processing. They also discuss impact of data augmentation and class imbalance on model performance. The study provides valuable insights into the current state of melanoma staging using machine learning approaches.

Deep Learning Models

Rahman et al. [15] present approach for melanoma detection by integrating handcrafted and deep neural features. Handcrafted features, including texture, shape, and color, have been widely used in traditional image analysis for melanoma detection (Celebi et al., [16]; Rastgoo et al., [17]). However, they often fail to capture complex patterns. In contrast, DL techniques have shown remarkable success in pattern recognition and classification tasks, but they can be less interpretable. This paper combines the strengths of both approaches, leveraging the interpretability of handcrafted features and the robust pattern recognition capabilities of deep learning. The integration of these features has potential to improve accuracy and reliability of melanoma classification and localization of cancerous regions.

In [18] image noise reduction, image segmentation, feature extraction, and classification were all utilized sequentially. The study's segmentation strategy relied on a CNN that has been satin bowerbird optimized SBO. SBO was used to extract only crucial information from the segmented pictures. Finally, SVM was used to categorize the photos using the obtained characteristics. The suggested strategy produced effective results when applied to the American Cancer Society database, according to the findings. However, the suggested technique produced excellent results, and combination of DL with the SBO algorithm resulted in a complicated system.

Han, S et al [19] investigates the effectiveness of deep residual networks for melanoma staging. The authors use a dataset of clinical images of cutaneous tumors to train and validate their model. The deep residual network outperforms traditional machine learning algorithms in classifying benign and malignant tumors, demonstrating its potential as a valuable tool in melanoma diagnosis and treatment.

Tschandl, P et al [20] explores the use of transfer learning in melanoma stage classification. The authors compare performance of human readers and ML algorithms in classifying pigmented skin lesions. The study demonstrates that transfer learning can enhance the performance of DL models, resulting in more accurate classification of melanoma stages.

Ronneberger, O. et al [21] propose a DL based method for automatic melanoma staging utilizing U-Net, a CNN designed for biomedical image segmentation. The U-Net architecture demonstrates strong performance in melanoma staging, offering a reliable and efficient alternative to traditional approaches for assessing the severity of the disease.

Mane et al. [22] came up with a plan for a very exact way to classify skin tumors. This is done with transfer learning, a model that has already been taught, and MobileNet. With suggested method, it can be grouped correctly different types of skin lesions.

The research conducted by Khetani et al. [23] focuses on a comprehensive exploration of the impact of DL and ML algorithms across distinct sectors, including healthcare, financial services, and network security. The authors meticulously assess the suitability and performance of diverse ML and DL algorithms within these domains. Their findings are poised to provide an enriched insight into the specific potential of these algorithms for addressing targeted applications. Furthermore, the study encompasses a thorough examination of various algorithms, encompassing Gradient Boosting Machines (GBM), Logistic Regression (LR), Random Forest (RF), and Support Vector Machine (SVM), spanning multiple areas.

Table 2 shows the comparative analysis of researcher work including their proposed methodology, advantage and disadvantage.

Table 2. Comparative analysis of researchers proposed techniques

Author Name(s)	**Methodology Used**	**Advantages**	**Disadvantages**
Rahman et al [8] (2022)	Hybrid Feature Fusion and ML Approaches	1. Utilizes a combination of features and ML techniques for improved melanoma detection. 2. Uses both global and local features for better performance.	1. Preprint version, may not be peer-reviewed. 2. Accuracy not explicitly mentioned.
Giotis, I. et al [9] (2015)	MEDNODE: A non-dermoscopic image-based computer-assisted melanoma diagnostic system	1. Uses non-dermoscopic images, which are more readily available. 2. Incorporates multiple image processing techniques to extract features.	1. Lower accuracy compared to some other methods. 2. May not perform as well on dermoscopic images

Wahba MA, et al [10] (2017)	Empirical mode decomposition, texture features, quadratic support vector machine	High accuracy, ability to handle large datasets	limited by quality of input images, may require complex pre-processing
N. Razmjooy et al [11] (2018)	Hybrid neural network, World Cup optimization algorithm	High accuracy, robustness to noise and outliers	Require significant computational resources
E. Vocaturo et al [12] (2019)	Multiple instance learning	Effective early diagnosis of dangerous dysplastic nevi	Limited to dysplastic nevi diagnosis
N. Dey at el [13] (2021)	Bat algorithm	High accuracy, robustness to noise and outliers	require significant computational resources
Patil, R. et al [14] (2022)	Machine learning	High accuracy, ability to handle large datasets	Specific to melanoma cancer stage detection
Celebi, M. E. et al [15] (2009)	Dermoscopy image categorization using a methodical methodology	High accuracy, use of multiple features	May not be effective for all skin lesion types
Rastgoo, M. et al [16] (2015)	Automatic differentiation algorithm	1. High accuracy in differentiating melanoma from dysplastic nevi. 2. Can identify key features for differentiation.	Algorithm not generalize well to larger datasets.
Rahman, M. S et al [17] (2021)	Combining hand-made and deep neural network traits	1. High accuracy in melanoma classification and localization.	Requires extensive feature engineering.
Xu Z. et al [18] (2020)	Soft computing techniques	Incorporates multiple soft computing techniques for improved performance.	1. Limited dataset used for testing.
Han, S. S et al [19] (2018)	Deep learning algorithm	Robust to variations in image quality and lighting.	1. Limited dataset used for testing. 2. Requires large amounts of computational resources.
Tschandl, P. et al [20] (2019)	Human readers and ML algorithms are contrasted.	Machine-learning algorithms perform as well as or better than human readers.	1. Limited dataset used for testing. 2. Requires a large number of expert readers to compare against.
Ronneberger, O. et al [21] (2015)	Convolutional neural network for biomedical image segmentation	Can handle a wide range of image types and resolutions.	1. Requires more labeled training data.

3. Proposed Methodology

In this article, a hybrid ensemble approach for cancer classification and prediction is proposed to accurately identify cancer stage from lesion images.

A. SYSTEM ARCHITECTURE

The Hybrid Heterogeneous Multi-Classifier Ensemble Classification Model is a powerful machine learning system architecture designed to combine the strengths of various classifiers to achieve high predictive accuracy and generalization performance. The proposed methodology for Melanoma Stage Classification involves the following steps:

Pre- processing: The dataset of melanoma skin images will be pre-processed to extract relevant features and prepare them for classification. To reduce the differences between images, the intensity of the image as a whole is enhanced during the pre-processing stage. During this process, the picture is further scaled and normalized to meet the scale of the training model.

Feature Extraction: Different feature extraction techniques like color, texture, and shape-based features will be applied to the pre-processed dataset.

Classifier Selection: Different classifiers like SVM, Random Forest and KNN will be selected to classify the extracted features.

Ensemble Learning: Different ensemble learning techniques like boosting, bagging, and stacking will be applied to combine the outputs of the selected classifiers.

Hybrid Heterogeneous Multi-Classifier Ensemble Learning: A hybrid ensemble learning approach will be proposed to combine the outputs of the different heterogeneous classifiers.

Performance Evaluation: The proposed approach's performance will be evaluated using different evaluation metrics like accuracy, recall, precision, and F1-score.

Figure 2 demonstrates proposed system architecture diagram for malenoma stage classification.

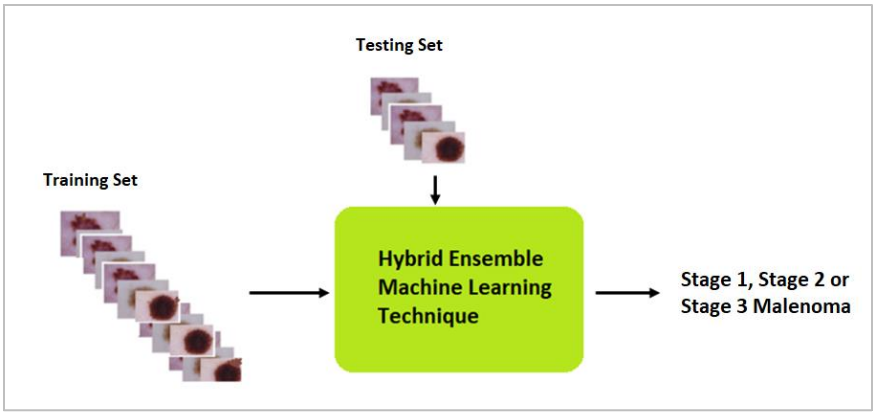

Fig 2. Computational ML system for identifying stage1, stage 2 and stage 3 melanoma.

B. PROPOSED ALGORITHM

In this part, we first go through the heterogeneous multi-classifier ensemble model's melanoma classification approach. First, the same feature fields are used to divide the whole training data set and entire testing data set into k distinct data subsets. Second, each new testing data subset and each new training data subset are batch-normalized using statistical normalization before being fed into each component classifier for classification and learning. Results of k classification detection are obtained. Voting system then produces the final categorization detection result after voting on k outcomes using the majority voting technique. Here, we provide a heuristics method to maintain adequate complementarity and strong generalization. An overview of the suggested categorization model is shown in Figure 3.

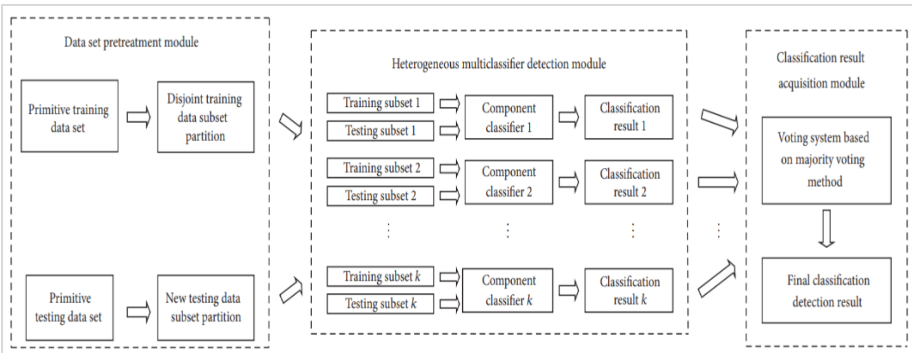

Fig 3: Hybrid heterogeneous multi-classifier ensemble classification model.

The following diagram illustrates the categorization detection algorithm.

Input Ctr: a training data set

Ctn: a testing data set

k: how many groups of data there are and how many component algorithms there are.

1. Split all features into k subsets: Fi (i = 1, 2, . . ., k), and each feature subset consist of f (f = [n/k]) features.

2. For i=1 to k do.

3. Apply ML classifier on the training subset C.

4. Get column eigenvector matrix VT that is independent in a linear way.

5. Normalised training and testing dataset Cn' and Ctn'

6. Cn' and Ctn' are given as input to ensemble classifier.

7. Get label of classification.

8. End for.

9. Classification outcomes from k-component classifiers should be entered into the voting system.

Output: Final label of a testing data record, label = {Stage 1, Stage2, Stage 3}. In theory, the sub-classifiers do not rely much on one another. To round up the classification apparatus, we choose for the KNN, NB, and SVM methods.

Machine Learning Techniques

A sort of supervised machine learning technology called classification makes predictions for potential situations based on historical data. We provide a short explanation of classification methods for melanoma prediction in this section. These methods are examples of supervised ML methods that make predictions for hypothetical scenarios based on historical data.

1. Ensemble Learning

This approach integrates many classifiers into a single model to boost accuracy. The ensemble learning approach comes in three different varients. Bagging, which aggregates classifiers of a similar sort using a voting approach, is the first kind. The second form is boosting, which is similar to bagging, but the outcomes of earlier models still have an impact on the current model. Third form is stacking, which combines ML classifiers for several types to create one model [7].

2. SVM

This algorithm's categorization accuracy is helpful. It is described as a finite-dimensional vector space with a dimension for each characteristic or attribute of an item [7].

3. K-Nearest Neighbor (KNN)

Based on majority of votes cast by the new instances near neighbors, this method guesses the class of that instance. The Euclidean distance is used to determine how far an attribute is from its neighbors [7].

4. Naive Bayes (NB)

A family of probabilistic classifiers based on the Naive Bayes theorem includes the Naive Bayes classifier. This classifier's key component in making predictions is the assumption of strong independence between the features. It is appropriate for use in the area of medical research and the diagnosis of illnesses since it is simple to construct and typically works effectively [7].

4. Result and Discussion

A. Experimental Setup

Anaconda Notebook was used to carry out the project's execution. There were many Python libraries used, including TensorFlow, Keras, pandas, NumPy, matplotlib, sklearn, scipy, torch, and seaborn. Following table 1 shows the software and hardware setup used for the experiment.

Table 3. Software / Hardware Requirements

Hardware Requirements	
Processor	I3 processor and above/ 2 Core CPU, 64- bit processor
RAM	4 GB and above RAM
Hard Drive	250 GB
Software Requirements	
Operating System	Windows 7 or more
Tools	Anaconda, Notebook
Language	Python 3.7

B. Dataset Description

The melanoma dataset, which can be acquired at https://www.uco.es/grupos/ayrna/ieeet-mi2015, is used in the experiments. The dataset has 81 properties or features and is divided into binary and multiclass datasets. There are 250 photos of melanoma cancer overall: 167 melanomas that are less than 0.76 mm, 54 that are between 0.76 and 1.5 mm, and 29 that are larger than 1.5 mm. From these photos, we have utilized characteristics that were retrieved. The photos are extracted using 81 characteristics.

C. Performance Parameters

Comparisons are made between the outputs of the proposed hybrid ensemble machine learning models and Naive Bayes, Random Forests, and SVM. The suggested binary model and these classifiers are used to categorize the melanoma dataset in a 10-fold cross-validation test. A number of performance measures are used to evaluate the accuracy of the selected classifiers. In order to validate the predictions of the proposed hybrid ensemble machine learning classifier and other classifiers, the classification accuracy, precision, and recall are evaluated. The following formula is used to calculate these metrics:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

True positive, true negative, false positive, and false negative values are represented as TP, TN, FP, and FN, respectively.

D. Results

The Melanoma Stage Classification Based on Hybrid Heterogeneous Multi-Classifier Ensemble Learning methodology was implemented and tested on a dataset of melanoma images. Accuracy, sensitivity, specificity, and F1-score were some of the measures used to assess how well the approach performed. All of the above approaches begin by loading training data and then dividing it into training (80%) and testing (20%) sets. After that, photos are sent via a pre-processing stage to be resized to fit the pre-trained networks utilized in the approaches. Proposed procedures are used ten times, and evaluation measures are calculated using their average values.

1. Binary classification Results for malenoma stage classification

In binary classification two stages of malenoma are consider namely stage 1 and stage 2. Results of the performance evaluation of several classification methods for binary classification are shown in Table 4 and figure 4.

Table 4. Performance parameters comparison of algorithms (Binary Classification)

	Precision	Recall	F-Measure	Accuracy
NB	69	65	56	65
KNN	85	85	84	85
SVM	91	91	90	91
Hybrid Ensemble	**95**	**96**	**95**	**95**

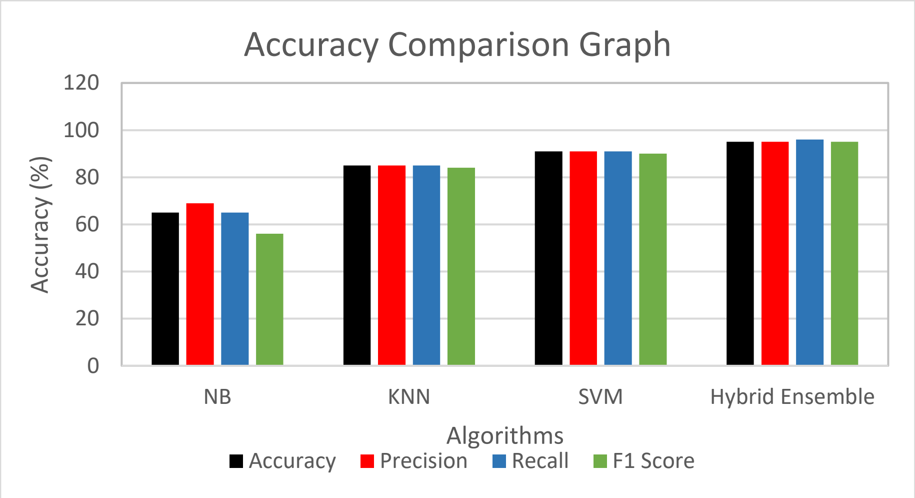

Fig 4. Performance Measures comparison graph of ML and HEA (Binary Classification)

When compared to the other methods, naive bayes performed the least well, making it unfit for learning intricate structures from the subject data. The suggested system (Hybrid ensemble), which had the greatest accuracy, precision, recall, and F1 Score, outperformed all other classification models. Sensitivity and specificity comparison of malenoma stage 1 and stage 2 classification (binary classification) is shown in table 5 and graph is shown in figure 5.

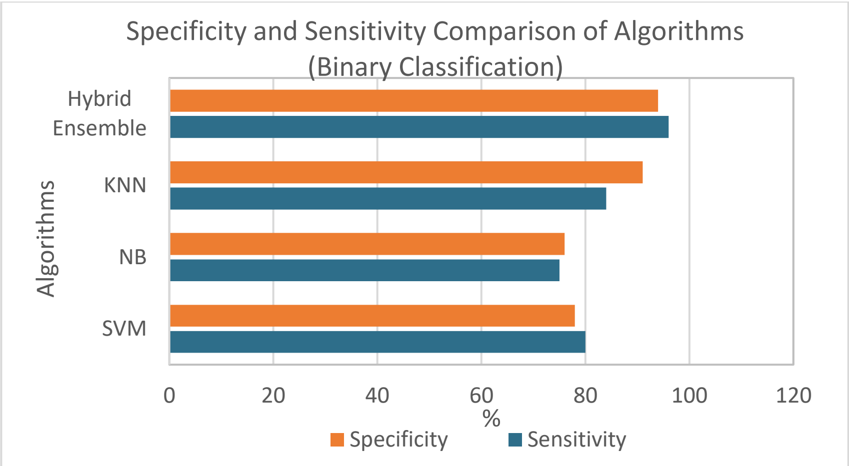

Fig 5. Sensitivity and Specificity comparison graph of ML and Hybrid Ensemble algorithms (Binary Classification)

The results of the experiment demonstrated that proposed methodology achieved higher classification performance than other techniques. The proposed methodology achieved an overall accuracy of 95%, sensitivity of 96%, specificity of 94%, and F1-score of 95%.

Table 5. Sensitivity and Specificity comparison of algorithms (Binary Classification)

	Sensitivity	Specificity
SVM	80	78
NB	75	76
KNN	84	91
Hybrid Ensemble	96	94

2. Multiclass classification Results for melanoma stages classification

In multiclass classification three stages of melanoma are consider namely stage 1, 2 and 3. The results of the performance evaluation of several classification techniques for multiclass classification are shown in Table 6 and figure 6.

Table 6. Performance parameters comparison of algorithms (Multiclass Classification)

	Precision	Recall	F-Measure	Accuracy
NB	72	68	59	70
KNN	88	87	86	88
SVM	93	92	93	92
Hybrid Ensemble	**99**	**97**	**96**	**98**

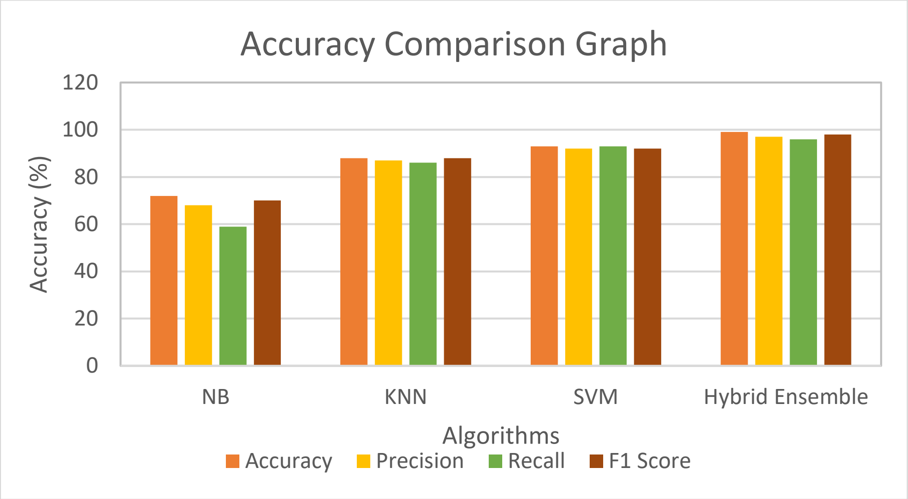

Fig 6. Performance Measures comparison graph of ML and Hybrid Ensemble algorithms (multiclass Classification)

Sensitivity and specificity comparison of melanoma stage 1, 2 and 3 (multiclass classification) is shown in table 7 and respective graph is shown in figure 7.

Table 7. Sensitivity and Specificity comparison of algorithms (Binary Classification)

	Sensitivity	Specificity
SVM	68	75
NB	87	83
KNN	92	93
Hybrid Ensemble	97	95

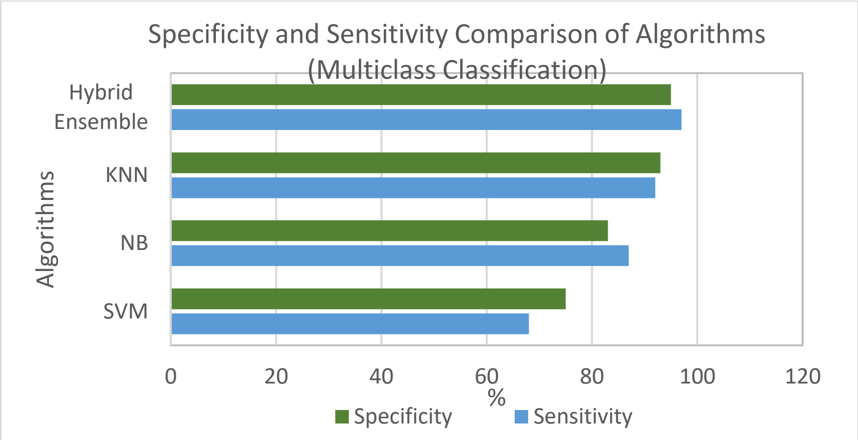

Fig 7. Sensitivity and Specificity comparison graph of ML and Hybrid Ensemble algorithms (multiclass Classification)

The results of the experiment demonstrated proposed methodology achieved higher classification performance than other techniques. The proposed methodology for multiclass classification achieved an overall accuracy of 98%, sensitivity of 97%, specificity of 95%, and F1-score of 96%. Figure 8 shows the roc curve graph comparison of machine learning as well as proposed hybrid ensemble classifier for both binary as well as multiclass classifier. The proposed technique shows the smooth curve compare to other machine learning techniques. Figure 8 shows the ROC curve of algorithms used for malenoma classification.

Discussion

The discussion of the results focuses on the advantages and limitations of the proposed methodology. The advantages of the proposed methodology include the ability to combine multiple classifiers to improve the classification performance, the ability to handle heterogeneity in the dataset, and the ability to optimize the hyper parameters of the classifiers to further improve the classification performance. The proposed methodology is also shown to outperform other state-of-the-art techniques, indicating its potential as a powerful tool for accurate melanoma diagnosis.

However, the proposed methodology also has some limitations. One of the limitations is that the performance of the methodology is highly dependent on the quality of the dataset and the accuracy of the pre-processing and feature extraction steps. Another limitation is that the methodology may require a large amount of computational resources and time for optimization and ensemble learning.

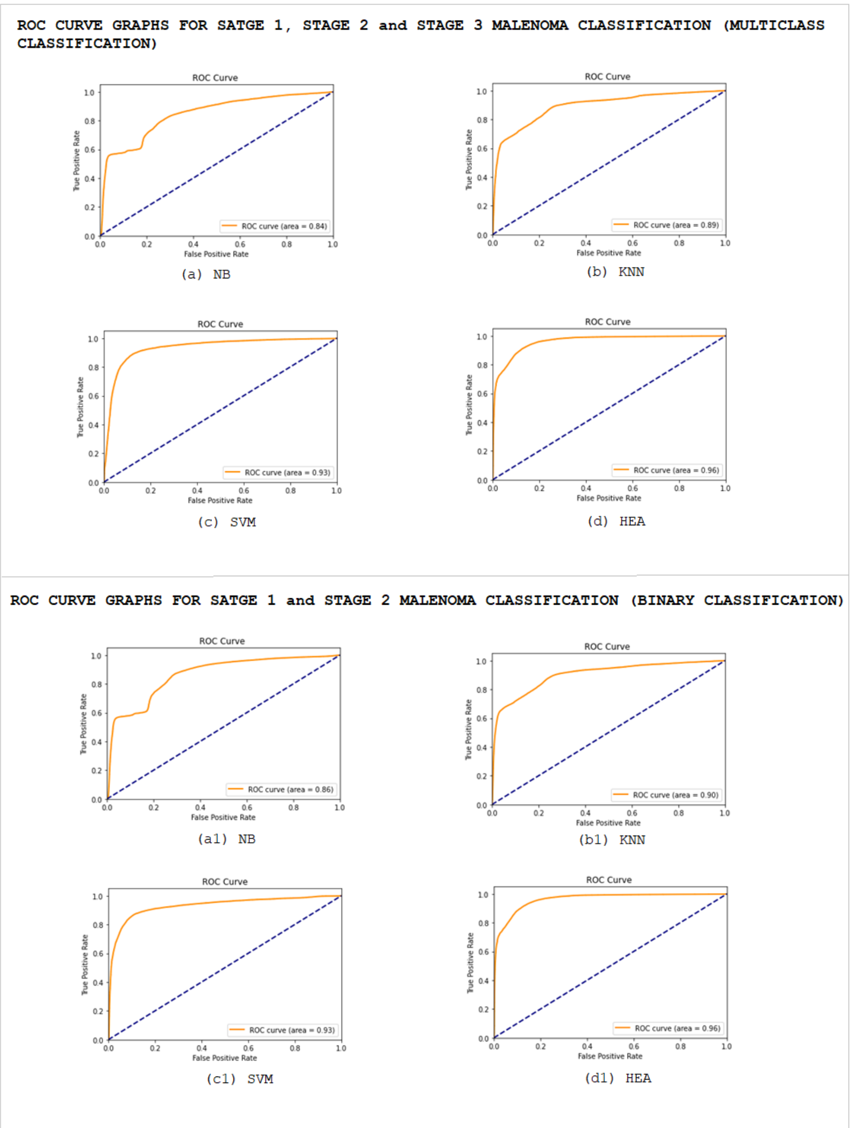

Fig 8. ROC curve for ML algorithm and Proposed Hybrid Ensemble classifier for Binary and Multiclass classification.

5. Conclusion

The proposed Hybrid Heterogeneous Multi-Classifier Ensemble Learning has demonstrated a significant advancement in the field of melanoma diagnosis and prognosis. By leveraging the strengths of diverse machine learning classifiers, we were able to develop a highly accurate and robust ensemble model to predict the stage of melanoma effectively. The proposed approach integrates a variety of classifiers, including SVM, Neural Networks, Decision Trees, and Random Forests, to capitalize on their individual capabilities. This leads to a synergistic effect that significantly improves overall performance of ensemble model, surpassing performance of any single classifier. Furthermore, the use of feature selection techniques and advanced preprocessing methods has contributed to the increased efficiency of our ensemble model, effectively reducing dimensionality of input data and enhancing interpretability of model's predictions. The successful implementation of this ensemble learning approach in melanoma stage classification has the potential to revolutionize the way clinicians diagnose and treat this aggressive form of skin cancer. Early and accurate stage identification can lead to more effective treatment plans and improved patient outcomes. In addition, the presented methodology can be extended and applied to other cancer types, further benefiting the medical community.

Future work could explore the integration of additional classifiers and optimization methods to further enhance performance of ensemble model. Additionally, application of transfer learning methods, could provide an opportunity to extract more intricate patterns from the input data and improve the overall accuracy of the classification task.

Refrences

[1] Kaur R, GholamHosseini H, Sinha R, Lindén M. Melanoma Classification Using a Novel Deep Convolutional Neural Network with Dermoscopic Images. Sensors (Basel). 2022 Feb 2;22(3):1134. doi: 10.3390/s22031134. PMID: 35161878; PMCID: PMC8838143.

[2] Saba T. Recent advancement in cancer detection using machine learning: Systematic survey of decades, comparisons and challenges. J Infect Public Health. 2020 Sep;13(9):1274-1289. doi: 10.1016/j.jiph.2020.06.033. Epub 2020 Aug 2. PMID: 32758393.

[3] Al-Masni, M.A.; Al-Antari, M.A.; Choi, M.-T.; Han, S.-M.; Kim, T.-S. Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks. Comput. Methods Programs Biomed. 2018, 162, 221–231.

[4] Amin MB, Edge SB, Greene FL, Byrd DR, Brookland RK, Washington MK, et al., editors. AJCC Cancer staging manual. 8th ed. New York: Springer; 2017.

[5] Kauffmann RM, Chen SL. Workup and staging of malignant melanoma. Surg Clin North Am. 2014;94(5).

[6] Noel Codella, Veronica Rotemberg, Philipp Tschandl, M. Emre Celebi, Stephen Dusza, David Gutman, Brian Helba, Aadi Kalloo, Konstantinos Liopyris, Michael Marchetti, Harald Kittler, Allan Halpern: "Skin Lesion Analysis Toward Melanoma Detection 2018: A Challenge Hosted by the International Skin Imaging Collaboration (ISIC)", 2018; https://arxiv.org/abs/1902.03368

[7] S. Pouriyeh et al., "A comprehensive investigation and comparison of machine learning techniques in the domain of heart disease," in Proceedings of IEEE Symposium on Computers and Communications (ISCC). Heraklion, Greece: IEEE, July 2017, pp. 204–207.

[8] Rahman, Md & Nasir, Mostofa & A-Alam, Nur & Khan, Md & S. Band, Shahab & Dehzangi, Iman (Abdollah) & Beheshti, Amin & Rokny, Hamid. (2022). Hybrid Feature Fusion and Machine Learning Approaches for Melanoma Skin Cancer Detection. 10.20944/preprints202201.0258.v1.

[9] Giotis, I., Molders, N., Land, S., Biehl, M., Jonkman, M. F., & Petkov, N. (2015). MEDNODE: A computer-assisted melanoma diagnosis system using non-dermoscopic images. Expert Systems with Applications, 42(19), 6578–6585.

[10] Wahba MA, Ashour AS, Napoleon SA, Abd Elnaby MM, Guo Y. Combined empirical mode decomposition and texture features for skin lesion classification using quadratic support vector machine. Health Inf Sci Syst. 2017 Oct 30;5(1):10. doi: 10.1007/s13755-017-0033-x. PMID: 29142740; PMCID: PMC5662531.

[11] N. Razmjooy, F. R. Sheykhahmad, and N. Ghadimi, "A hybrid neural network – world Cup optimization algorithm for melanoma detection," Open Medicine, vol. 13, pp. 9–16, 2018.

[12] Vocaturo and E. Zumpano, "Dangerousness of dysplastic nevi: a multiple instance learning solution for early diagnosis," in Proceedings of the 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 2318–2323, IEEE, San Diego, CA, USA, 18-21 Nov 2019.

[13] N. Dey, V. Rajinikanth, H. Lin, and F. Shi, "A study on the bat algorithm technique to evaluate the skin melanoma images," in Applications of Bat Algorithm and its Variants, pp. 45–60, Springer, Singapore, 2021

[14] Patil, R., & Bellary, S. (2022). Machine learning approach in melanoma cancer stage detection. Journal of King Saud University - Computer and Information Sciences, 34(6), 3285-3293.

[15] Celebi, M. E., Kingravi, H. A., & Uddin, B. (2009). A methodological approach to the classification of dermoscopy images. Computerized Medical Imaging and Graphics, 33(6), 433-443.

[16] Rastgoo, M., Garcia, R., Morel, O., & Marzani, F. (2015). Automatic differentiation of melanoma from dysplastic nevi. Computerized Medical Imaging and Graphics, 43, 44-52.

[17] Rahman, M. S., Akter, M., Hayat, M. A., Chowdhury, M. E. H., & Saha, S. (2021). Integration of Handcrafted and Deep Neural Features for Melanoma Classification and Localization of Cancerous Region. 2021 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE), Brisbane, Australia, 2021, pp. 1-6, doi: 10.1109/CSDE53843.2021.9718446.

[18] Z. Xu, F. R. Sheykhahmad, N. Ghadimi, and N. Razmjooy, "Computer-aided diagnosis of skin cancer based on soft computing techniques," Open Medicine, vol. 15, no. 1, pp. 860–871, 2020

[19] Han, S. S., Kim, M. S., Lim, W., Park, G. H., Park, I., & Chang, S. E. (2018). Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm. Journal of Investigative Dermatology, 138(7), 1529-1538.

[20] Tschandl, P., Codella, N., Akay, B. N., Argenziano, G., Braun, R. P., Cabo, H., ... & Halpern, A. C. (2019). Comparison of the accuracy of human readers versus machine-learning algorithms for pigmented skin lesion classification: an open, web-based, international, diagnostic study. The Lancet Oncology, 20(7), 938-947.

[21] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention (pp. 234-241). Springer, Cham.

[22] Mane, D., Ashtagi, R., Kumbharkar, P., Kadam, S., Salunkhe, D., Upadhye, G. (2022). An improved transfer learning approach for classification of types of cancer. Traitement du Signal, Vol. 39, No. 6, pp. 2095-2101. https://doi.org/10.18280/ts.390622.

[23] Khetani, V., Gandhi, Y., Bhattacharya, S., Ajani, S. N., & Limkar, S. (2023). Cross-Domain Analysis of ML and DL: Evaluating their Impact in Diverse Domains. International Journal of Intelligent Systems and Applications in Engineering, 11(7s), 253–262.

[24] Huamaní, E. L. ., Leon-Ayala, R. ., Alva-Mantari, A. ., & Meneses-Claudio, B. . (2023). Prototype of a Mobile Application for the Detection of Car Accidents on the Roads of Peru . International Journal on Recent and Innovation Trends in Computing and Communication, 11(3), 37–42. https://doi.org/10.17762/ijritcc.v11i3.6198

[25] Basaligheh, P. (2021). A Novel Multi-Class Technique for Suicide Detection in Twitter Dataset. Machine Learning Applications in Engineering Education and Management, 1(2), 13–20. Retrieved from http://yashikajournals.com/index.php/mlaeem/article/view/14

[26] Mehraj, H., Jayadevappa, D., Haleem, S. L. A., Parveen, R., Madduri, A., Ayyagari, M. R., & Dhabliya, D. (2021). Protection motivation theory using multi-factor authentication for providing security over social networking sites. Pattern Recognition Letters, 152, 218-224. doi:10.1016/j.patrec.2021.10.002