

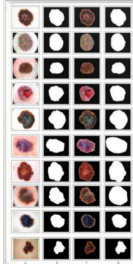
Department of Computer Science and Engineering
Bangladesh University of Business and Technology (BUBT)



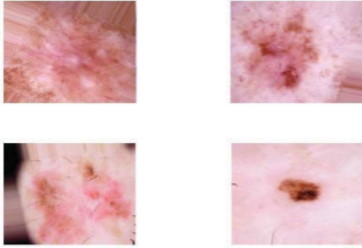
CSE 498: Literature Review Records

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Capstone Project Title	Skin Cancer Detection using Neural Network
Supervisor Name & Designation	Name: Dr. Md.Rajibul Islam & Designation: Associate Professor, Department of CSE, BUBT
Course Teacher's Name & Designation	Name: Khan Md. Hasib & Designation: Assistant Professor, Department of CSE, BUBT

Aspects	Paper # 1 (Title)
Title / Question (What is problem statement?)	Skin Cancer Classification Using Image Processing and Machine Learning
Objectives / Goal (What is looking for?)	The paper proposes a method for accurately detecting early-stage melanoma using image processing and machine learning. It includes contrast stretching, OTSU thresholding, and feature extraction techniques. The method addresses class imbalance and reduces dimensionality using PCA and SMOTE. A novel feature selection approach is introduced. The proposed method achieves a maximum accuracy of 93.89% using the Random Forest classifier on the ISIC-ISBI 2016 dataset.
Methodology / Theory (How to find the solution?)	<p>The proposed method aims to classify and segment skin lesions as benign or malignant using a combination of image processing and machine learning techniques. Here is a summarized version of the proposed methodology:</p> <ul style="list-style-type: none"> • Contrast stretching: Enhance image contrast using mean values and standard deviation of pixels. • Image segmentation: Use the OTSU thresholding algorithm to separate lesions from the background. • Feature extraction: Extract features including GLCM for texture, HOG for shape, and color identification features. • PCA reduction: Reduce dimensionality of HOG features using Principal Component Analysis. • SMOTE sampling: Address class imbalance problem by generating synthetic samples for the minority class. • Standardization and scaling: Normalize feature vector to ensure similar ranges. • Feature selection: Use the wrapper method to select the best subset of features for classification. • Classification: Utilize Quadratic Discriminant, SVM (Medium Gaussian), and Random Forest classifiers. • Evaluation: Verify the approach on the ISIC-ISBI 2016 dataset, achieving a maximum accuracy of 93.89% with Random Forest.
Software Tools (What program/software is used for design, coding and simulation?)	MIPAV, MATLAB, Python, OpenCV, and scikitlearn.

<p>Test / Experiment How to test and characterize the design/prototype?</p>	<p>The paper proposes a novel method of contrast stretching of dermoscopic images based on mean values and standard deviation of pixels, followed by the OTSU thresholding algorithm for image segmentation. Features including Gray level Co-occurrence Matrix (GLCM) features, Histogram of Oriented Gradients (HOG) object, and color identification features are extracted from the segmented images. Principal component analysis (PCA) reduction of HOG features is performed for dimensionality reduction, and Synthetic Minority Oversampling Technique (SMOTE) sampling is used to deal with the class imbalance problem. The feature vector is then standardized and scaled, and a novel approach of feature selection based on the wrapper method is proposed before classification. Classifiers including Quadratic Discriminant, SVM (Medium Gaussian), and Random Forest are used for classification. The proposed approach is verified on the publicly accessible dataset of ISIC-ISBI 2016, and the maximum accuracy is achieved using the Random Forest classifier with a classification accuracy of 93.89%. The paper also notes that the proposed approach of contrast stretching before segmentation gives satisfactory results of segmentation</p>								
<p>Simulation/Test Data (What parameters are determined?)</p>	<p>It uses a publicly accessible dataset, namely ISIC-ISBI 2016, for verification of the proposed approach. The accuracy of the proposed system with the Random Forest classifier on this dataset is reported to be 93.89%.</p> 								
<p>Result / Conclusion (What was the final result?)</p>	<p>The final result of the study was the development of a machine learning-based approach for skin lesion classification and segmentation as benign or malignant. The proposed approach achieved a maximum classification accuracy of 93.89% using the Random Forest classifier on the ISIC-ISBI 2016 dataset. The study also reported the confusion matrix using the Random Forest classifier, which showed that 93.9% of the total guesses were correct and 6.1% were erroneous. Overall, the study demonstrated the potential of machine learning techniques for accurate and early detection of skin cancer, which can improve the survival rate of patients.</p> <table border="1" data-bbox="727 1731 1232 1984"> <thead> <tr> <th>Classification Algorithm</th><th>Accuracy (%)</th></tr> </thead> <tbody> <tr> <td>SVM</td><td>88.17</td></tr> <tr> <td>Quadratic Discriminant</td><td>90.84</td></tr> <tr> <td>Random Forest</td><td>93.89</td></tr> </tbody> </table>	Classification Algorithm	Accuracy (%)	SVM	88.17	Quadratic Discriminant	90.84	Random Forest	93.89
Classification Algorithm	Accuracy (%)								
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<p>Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)</p>	<p>The paper mentions some challenges and obstacles, such as the class imbalance problem, where there are more examples of benign skin lesions than malignant ones, leading to biased results. The authors addressed this issue by using the synthetic minority oversampling technique (SMOTE) to generate synthetic examples of the minority class.</p>								

<p>Terminology (List the common basic words frequently used in this research field)</p>	<ul style="list-style-type: none"> • Synthetic minority oversampling technique (SMOTE) • Principal component analysis (PCA) • Random Forest • Support vector machines (SVM)
<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>The paper proposes a novel approach for skin lesion classification and segmentation using image processing and machine learning.</p> <p>The proposed method achieves high accuracy on the ISIC-ISBI 2016 dataset, which is a publicly accessible dataset for skin cancer detection. The paper also identifies some of the challenges in skin cancer diagnosis, such as the high cost of traditional methods and the need for expert dermatologists. Overall, the paper appears to contribute to the field of skin cancer diagnosis and may be of interest to researchers and practitioners in the field.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>The paper proposes a method for skin lesion classification and segmentation as benign or malignant using image processing and machine learning. The proposed approach is verified on the publicly accessible dataset of ISIC-ISBI 2016, and the maximum accuracy achieved using the Random Forest classifier is 93.89%.</p>

Aspects	Paper # 2 (Title)
Title / Question (What is problem statement?)	Analysis and Classification of Skin Cancer Images using Convolutional Neural Network Approach
Objectives / Goal (What is looking for?)	The goal of this paper is to propose an intelligent machine learning approach using deep learning (CNN) algorithm to classify different types of skin cancer, including Basal cell Carcinoma (BBC), Melanocytic Nevus (NV), and Vascular Lesion (VASC), based on their respective images. The paper argues that this approach could be a more reliable and efficient way to classify skin cancer, leading to early diagnosis and better accuracy in the field of medicine. The paper reports that the proposed approach achieved 98.89% accuracy in the classification of skin cancer types.
Methodology / Theory (How to find the solution?)	The methodology in this paper involves using CNN to classify skin cancer images based on their types. The dataset used in the study contains 3150 images, each with a size of 28x28 pixels and RGB format. The first convolutional layer has a filter size of 5x5 and a channel size of 8, with the same padding 2x2, followed by a max pooling layer with a stride of 2. Then, a second convolutional layer with a filter size of 3x3 and a channel size of 8, with the same padding 2x2, is applied, followed by another max pooling layer with a stride of 2. Finally, a fully connected layer is used to classify the skin cancer images.
Software Tools (What program/software is used for design, coding and simulation?)	Python and libraries such as TensorFlow or Keras were used, Image processing libraries and tools, Data augmentation tools.
Test / Experiment How to test and characterize the design/prototype?	<p>The test/experiment in the paper involves training the CNN algorithm using a dataset of skin cancer images and evaluating the classification accuracy of the algorithm. The dataset contains 3150 images with a size of 28x28 pixels and RGB format.</p> <pre> graph TD A[28x28x3 RGB Image] --> B[Deep Learning (CNN) Algorithms] B --> C[Basal cell Carcinoma (BBC)] B --> D[Melanocytic Nevus (NV)] B --> E[Vascular Lesion (VASC)] </pre> 

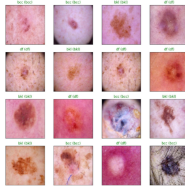
Simulation/Test Data (What parameters are determined?)	<p>The dataset includes images of three types of skin cancer, Basal cell Carcinoma (BBC), Melanocytic Nevus (NV), and Vascular Lesion (VASC). The images were preprocessed, including normalization and data augmentation, to improve the performance and accuracy of the CNN algorithm. The preprocessed images were then split into training and testing sets, with 80% of the images used for training and the remaining 20% used for testing. The CNN algorithm was trained on the training set for 10 epochs, and the testing set was used to evaluate the performance of the algorithm. The accuracy of the algorithm on the testing set was reported to be 95.79%.</p> <table><tr><th>No of Images</th><th>Layers</th><th>Epochs</th><th>Accuracy</th><th>Training Time</th></tr><tr><td>1050</td><td>1</td><td>6</td><td>97.12</td><td>2 min 7 sec</td></tr><tr><td>1050</td><td>2</td><td>6</td><td>95.58</td><td>1 min 30 sec</td></tr><tr><td>1050</td><td>3</td><td>6</td><td>93.92</td><td>32 sec</td></tr></table>	No of Images	Layers	Epochs	Accuracy	Training Time	1050	1	6	97.12	2 min 7 sec	1050	2	6	95.58	1 min 30 sec	1050	3	6	93.92	32 sec
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Result / Conclusion (What was the final result?)	<p>The final result of this paper is that the implementation of convolutional neural network (CNN) algorithms can improve the performance of digital applications for skin cancer classification. The study achieved a classification accuracy of 98.89% using a CNN architecture with three convolutional layers, which is higher than using two or one convolutional layers. Overall, the paper demonstrates the potential of using intelligent machines with deep learning algorithms for skin cancer classification, which could improve the accuracy and efficiency of skin cancer diagnosis</p>																				
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	<p>There are several obstacles and challenges associated with the paper, including:</p> <ul style="list-style-type: none">• Limited types of skin cancer: The study only focused on three types of skin cancer, Basal cell Carcinoma (BBC), Melanocytic Nevus (NV), and Vascular Lesion (VASC). There are many other types of skin cancer that could be included in future studies.• Variability in image quality: The quality of skin cancer images can vary depending on factors such as lighting conditions, camera quality, and image resolution. These factors can affect the accuracy of the CNN algorithm, and future studies could address this issue by standardizing the image acquisition process.																				
Terminology (List the common basic words frequently used in this research field)	<p>The paper describes the dataset used, which consists of 3150 RGB images with a size of 28x28 pixels. The CNN architecture used in the study is described in detail, including the number and type of layers (two convolutional, two max pooling, and one fully connected layer), filter sizes, channel sizes, padding, and stride. The training progress of the CNN is visualized in a plot that shows the validation accuracy and loss over 10 epochs.</p>																				

<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>Based on the information provided in the paper's abstract, the study seems to have successfully applied deep learning (CNN) algorithms to classify skin cancer images with a high accuracy rate of 98.89%. Additionally, the paper provides detailed information about the dataset, CNN architecture, and training progress, which can be useful for other researchers in the field of medical image analysis and computer-aided diagnosis. Nonetheless, a more thorough evaluation of the methodology and results of the study is necessary to make a conclusive judgment about the paper's overall quality and contribution to the field.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>The conclusion seems to be well-supported by the study's results. The authors have found that the performance of digital applications for skin cancer diagnosis can be improved by using convolutional neural network algorithms. They achieved a high classification accuracy of 98.89% using a CNN architecture with three convolution layers, which was better than using only one or two convolution layers. The authors also noted that the computational time increases as the number of layers and epochs of the CNN network increases. They suggest that a high-performance processor could be used to decrease the computational time for each process.</p>

Aspects	Paper # 3 (Title)																																																																																				
Title / Question (What is problem statement?)	Enhanced Dermatoscopic Skin Lesion Classification using Machine Learning Techniques.																																																																																				
Objectives / Goal (What is looking for?)	The objective of this paper is to focus on the classification of dermatoscopic skin lesions using machine learning algorithms. The authors have used the MNIST HAM 10000 dataset and have analyzed the accuracy of different machine learning algorithms. The paper is divided into two parts: first, the authors have balanced the dataset using the Synthetic Minority Oversampling Technique (SMOTE) to improve the accuracy of machine learning models. Second, they have compared the accuracy of different machine learning algorithms such as Decision Tree, Naïve Bayes, XGBoost, Random Forest, Support Vector Machine, and Logistic Regression algorithms.																																																																																				
Methodology / Theory (How to find the solution?)	The methodology of this paper involves the use of machine learning algorithms to classify dermatoscopic skin lesions. The authors have used the MNIST HAM 10000 dataset and have analyzed the accuracy of different machine learning algorithms. They have also balanced the dataset using the Synthetic Minority Oversampling Technique (SMOTE) to improve the accuracy of machine learning models. The authors have evaluated the performance of the models using various evaluation metrics such as Accuracy, f1-score, recall, precision, sensitivity, and specificity.																																																																																				
Software Tools (What program/software is used for design, coding and simulation?)	The paper used Anaconda for Python 3.8 as the programming environment, Scikit for the implementation of various machine learning algorithms, and Pandas for data manipulation. The MNIST HAM1000 dataset was used for the implementation, which is available through ISIC archive. The dataset consisted of 10015 images of 7 classes, and was in the form of a CSV file containing pixel values of the images in the dataset. The implementation was carried out on a Windows 64 machine with 8 GB RAM.																																																																																				
Test / Experiment How to test and characterize the design/prototype?	<p>The authors used SMOTE to balance the dataset and compared the performance of different machine learning models, including logistic regression, decision tree, random forest, KNN, SVM with linear and polynomial kernels, and Naive Bayes. The results of the experiment were presented in tables, showing the accuracy, f1-score, recall, precision, sensitivity, and specificity values for each model in both balanced and imbalanced datasets.</p> <table><thead><tr><th>Machine Learning Algorithms</th><th>Imbalanced (%)</th><th>Balanced (%)</th></tr></thead><tbody><tr><td>Logistic Regression</td><td>67.354</td><td>82.451</td></tr><tr><td>Naive Bayes</td><td>44.392</td><td>39.571</td></tr><tr><td>Random Forest</td><td>72.013</td><td>95.227</td></tr><tr><td>Decision tree (Entropy)</td><td>63.904</td><td>85.447</td></tr><tr><td>Decision Tree (Gini)</td><td>61.457</td><td>83.896</td></tr><tr><td>SVM (kernel=Linear)</td><td>61.008</td><td>95.067</td></tr><tr><td>SVM (Kernal=Poly)</td><td>69.695</td><td>96.825</td></tr><tr><td>SVM (Kernal=rbf)</td><td>70.843</td><td>92.372</td></tr><tr><td>XGBoost</td><td>70.43</td><td>95.984</td></tr></tbody></table> <table><thead><tr><th>Machine Learning Algorithm</th><th>Precision (%)</th><th>Recall (%)</th><th>F1-Score (%)</th><th>Sensitivity (%)</th><th>Specificity (%)</th></tr></thead><tbody><tr><td>Logistic Regression</td><td>82</td><td>83</td><td>82</td><td>83.74</td><td>7.19</td></tr><tr><td>Naive Bayes</td><td>42</td><td>40</td><td>40</td><td>41.97</td><td>88.21</td></tr><tr><td>Random Forest</td><td>95</td><td>95</td><td>95</td><td>95.82</td><td>99.17</td></tr><tr><td>Decision Tree (Entropy)</td><td>85</td><td>86</td><td>85</td><td>86.03</td><td>97.58</td></tr><tr><td>Decision Tree (Gini)</td><td>85</td><td>85</td><td>85</td><td>85.87</td><td>97.59</td></tr><tr><td>SVM (Linear)</td><td>95</td><td>95</td><td>95</td><td>95.80</td><td>99.15</td></tr><tr><td>SVM (Polynomial)</td><td>97</td><td>97</td><td>97</td><td>97.29</td><td>99.45</td></tr><tr><td>SVM (RBF)</td><td>92</td><td>92</td><td>92</td><td>92.79</td><td>98.73</td></tr></tbody></table>	Machine Learning Algorithms	Imbalanced (%)	Balanced (%)	Logistic Regression	67.354	82.451	Naive Bayes	44.392	39.571	Random Forest	72.013	95.227	Decision tree (Entropy)	63.904	85.447	Decision Tree (Gini)	61.457	83.896	SVM (kernel=Linear)	61.008	95.067	SVM (Kernal=Poly)	69.695	96.825	SVM (Kernal=rbf)	70.843	92.372	XGBoost	70.43	95.984	Machine Learning Algorithm	Precision (%)	Recall (%)	F1-Score (%)	Sensitivity (%)	Specificity (%)	Logistic Regression	82	83	82	83.74	7.19	Naive Bayes	42	40	40	41.97	88.21	Random Forest	95	95	95	95.82	99.17	Decision Tree (Entropy)	85	86	85	86.03	97.58	Decision Tree (Gini)	85	85	85	85.87	97.59	SVM (Linear)	95	95	95	95.80	99.15	SVM (Polynomial)	97	97	97	97.29	99.45	SVM (RBF)	92	92	92	92.79	98.73
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Simulation/Test Data (What parameters are determined?)	The paper mentions that the MNIST HAM1000 dataset was used for the implementation of the proposed system, which is available through the ISIC archive. This dataset consists of 10015 images of 7 classes, including nevus lesions, dermatofibroma symptom, malignant skin tumors symptom, benign keratosis symptom, basal cell carcinoma symptom, actinic keratosis symptom, and vascular lesions symptom. The dataset is in the form of a CSV (Comma Separated Value) file, where the file contains the pixel values of images in the dataset. The dataset is an imbalanced dataset, with a huge difference between the majority and minority classes.
Result / Conclusion (What was the final result?)	The paper concludes that balancing the dataset with up-sampling using SMOTE improves the accuracy of the model. It also suggests that SVM with Polynomial kernel provides better accuracy compared to other machine learning algorithms for the classification of dermoscopic images. The authors plan to focus on the segmentation and feature extraction processes of dermoscopic images using deep learning models as input data in future work.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	Based on the paper, the main obstacle/challenge for the research is the imbalanced dataset, which is a common problem in many related works. Most of these works did not use balanced data or used a limited number of images, resulting in lower accuracy. To overcome this challenge, the proposed method used the standard HAM10015 dataset, which consists of 10015 skin lesion images with 7 categories. The researchers then used an up-sampling method called Synthetic Minority Oversampling Technique (SMOTE) to balance the dataset. Another challenge is the selection of the best machine learning algorithm for classification, which the researchers addressed by comparing several algorithms and selecting the one with the best accuracy.
Terminology (List the common basic words frequently used in this research field)	Some common basic words frequently used in this paper are: <ul style="list-style-type: none"> • Synthetic minority oversampling technique (SMOTE) • Comma Separated Value (CSV) • Support vector machines (SVM)
Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)	The paper, it seems to be a well-structured and informative study that addresses the problem of imbalanced data in skin lesion classification using machine learning algorithms. The authors have used a standard dataset and proposed an approach to balance the data using SMOTE, which improved the accuracy of the models. The paper provides detailed information on the methodology and results, making it useful for readers interested in the field of dermatology and machine learning.
Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	The accuracy of the SVM with Polynomial kernel is higher than all other algorithms, according to the author's research, which found that when $k=10$ was used in the k-fold cross validation algorithm, the accuracy was 95.984%

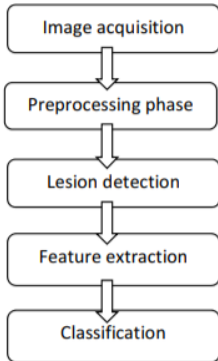
Aspects	Paper # 4 (Title)
Title / Question (What is problem statement?)	Skin Cancer Classification Model Based on VGG19 and Transfer Learning
Objectives / Goal (What is looking for?)	The goal of this paper is to investigate the use of convolutional neural networks (CNNs) in skin cancer diagnosis and classification. Specifically, the paper aims to classify two types of skin cancer and one non-cancer type using a CNN model based on VGG19 and transfer learning techniques. The paper discusses the training strategy, testing, and evaluation of the CNN model, including measuring the network's overall accuracy and loss. Overall, the objective of this paper is to demonstrate the potential of CNNs as autonomous feature extractors for improving the accuracy and efficiency of skin cancer diagnosis.
Methodology / Theory (How to find the solution?)	The methodology used in this paper involves using digital image processing and convolutional neural networks (CNNs) for skin cancer diagnosis and classification. Specifically, the study uses the Human Against Machine (HAM10000) dataset, which contains various types of skin cancer, to classify two cancer types (Dermatofibroma and Basal Cell Carcinoma) and one non-cancer type (Benign Keratosis-like Lesions) using a CNN model based on VGG19 and transfer learning techniques.
Software Tools (What program/software is used for design, coding and simulation?)	They use of pre-trained VGG19 model and Transfer Learning technique for skin cancer classification. The training and evaluation of the CNN model were done using Python programming language and popular deep learning libraries such as Keras and TensorFlow. Additionally, it mentions the use of Adam optimization function and a batch size of 50 for training the network.
Test / Experiment How to test and characterize the design/prototype?	In this paper, the proposed skin cancer classification system based on a convolutional neural network (CNN) was tested and evaluated using the Human Against Machine (HAM10000) dataset. The dataset contains various types of skin cancer, and two cancer types (Dermatofibroma and Basal Cell Carcinoma) in addition to one non-cancer type (Benign Keratosis-like Lesions) were selected for the study. The authors used a pre-trained VGG19 CNN model with fine-tuned parameters and applied transfer learning to classify the skin lesions into their respective categories. They split the dataset into 80% for training and 20% for testing, and used 20% of the training set for validation. They trained the network over 100 epochs with a batch size of 50 and a learning rate of 0.01, using the Adam optimization function. After training, they evaluated the network performance using overall accuracy and loss on a separate testing set of 600 images.
Simulation/Test Data (What parameters are determined?)	The paper uses the Human Against Machine (HAM10000) dataset for training and testing the CNN model. This dataset contains various types of skin lesions, including malignant and benign. Two types of skin cancer were selected from the dataset: Dermatofibroma (DF) and Basal Cell Carcinoma (BCC), in addition to one non-cancer type Benign Keratosis-like Lesions (BKL). However, there was an imbalance in the dataset because BKL was more common than the other two. After augmentation, each skin cancer type had 1000 samples in the dataset, and the final size of the dataset was 3000.

Result / Conclusion (What was the final result?)	<p>The result of the paper is that a VGG19-based Convolutional Neural Network (CNN) with transfer learning was trained to classify three types of skin cancer with high accuracy. The overall accuracy and loss of the network were evaluated using 600 test images and found to be satisfactory with an accuracy of 0.975 and a loss of 0.119.</p> <div></div> <table><tr><th rowspan="2">Epoch</th><th colspan="2">Training</th><th colspan="2">Validation</th></tr><tr><th>Accuracy</th><th>Loss</th><th>Accuracy</th><th>Loss</th></tr><tr><td>25</td><td>0.9823</td><td>0.1094</td><td>0.9708</td><td>0.1264</td></tr><tr><td>50</td><td>0.9849</td><td>0.0997</td><td>0.9750</td><td>0.1188</td></tr><tr><td>100</td><td>0.9859</td><td>0.0991</td><td>0.9750</td><td>0.1185</td></tr></table>	Epoch	Training		Validation		Accuracy	Loss	Accuracy	Loss	25	0.9823	0.1094	0.9708	0.1264	50	0.9849	0.0997	0.9750	0.1188	100	0.9859	0.0991	0.9750	0.1185
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25	0.9823	0.1094	0.9708	0.1264																					
50	0.9849	0.0997	0.9750	0.1188																					
100	0.9859	0.0991	0.9750	0.1185																					
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	<p>There are several obstacles and challenges that the paper may have faced during its development and implementation. Some of these challenges include:</p> <p>Data availability and quality: The paper’s success in training a CNN model relies heavily on the availability and quality of data. Inaccurate or incomplete data can hinder the network’s ability to learn and make accurate predictions.</p> <p>Overfitting: Overfitting occurs when a model becomes too complex and fits the training data too well, leading to poor performance on new, unseen data. This can be a challenge in training CNN models, especially when the dataset is small.</p> <p>Hardware limitations: CNN models are computationally expensive and require powerful hardware, such as GPUs, to train efficiently. Limited access to high-performance computing resources can be a significant challenge for researchers working on this type of project.</p>																								
Terminology (List the common basic words frequently used in this research field)	<ul style="list-style-type: none">• Convolutional Neural Network (CNN)• Transfer Learning (TL)• Basal Cell Carcinoma (BCC)• Dermatofibroma (DF)• Benign Keratosis-like Lesions (BKL)																								

<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>The paper appears to present a promising approach for classifying different types of skin cancer using a VGG19-based convolutional neural network. The authors provide detailed information about the training and testing process, including performance metrics, graphs, and a confusion matrix, which suggests that the network is performing well and is not overfitting. The authors also suggest future directions for their research, including expanding the range of skin cancer types studied and implementing additional preprocessing steps to improve accuracy further.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>The training and testing accuracy of the network were reported to be 0.985 and 0.975, respectively, while the training and testing loss were 0.099 and 0.119, respectively. The paper also indicates that the network is not overfitting, and the loss and accuracy have stabilized. The confusion matrix shows that the majority of predictions fall into the correct categories, with only a few incorrect predictions. Overall, the results indicate a satisfactory outcome that can be improved further.</p>

Aspects	Paper # 5 (Title)
Title / Question (What is problem statement?)	Skin cancer detection from dermoscopic images using deep learning and fuzzy k-means clustering
Objectives / Goal (What is looking for?)	Automated detection melanoma skin cancer at early stage and remove limitations from the existing techniques using RCNN along with FKM. Existing techniques limitations: (a)high computational cost; (b) model overfitting problem.
Methodology / Theory (How to find the solution?)	The methodology presented in the paper involves a new method for detecting and segmenting skin lesions using faster-RCNN along with FKM clustering. The process involves preprocessing the input images to eliminate artifacts such as illumination and noise effects, followed using the faster-RCNN algorithm for identifying the melanoma portion. After the detection process, FKM clustering is employed to segment the affected part of the image, which can be later used for melanoma disease recognition. The feature extraction process uses the faster-RCNN algorithm, which is a deep-learning framework that automatically extracts efficient and discriminative features from the input image based on labeled training data, without the need for a hand-coded feature selection method.
Software Tools (What program/software is used for design, coding and simulation?)	Not mentioned
Test / Experiment How to test and characterize the design/prototype?	<ul style="list-style-type: none"> • The ISIC-2016 dataset: total 1,280 images; 900 images are for training purposes; 380 images are used for testing the presented method. • The ISIC-2017 dataset: 2000 training samples; 150 samples for validation and 600 images for testing. • PH2 dataset: 200 samples with 40 images of melanomas (private data)
Simulation/Test Data (What parameters are determined?)	Image data
Result / Conclusion (What was the final result?)	Accuracy: <ul style="list-style-type: none"> • ISIC2016 : 95.40 • ISIC2017 : 93.1 • PH2 : 95.6
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	Future work isn't mentioned in the article.
Terminology (List the common basic words frequently used in this research field)	deep learning, faster-RCNN, fuzzy c-means clustering, melanoma, skin cancer, FKM

<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>Detecting skin cancer at early stage is the biggest challenges now-a-days. The work shows that accuracy is higher than existing models and also the proposed model overcome the existing model's limitations. On the other hand, the followed methodology has more accuracy then existing models.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>The outcome of this work is great, and the proposed model has a good result. Hope the proposed model will be able to obtain a good result on other types of skin cancer. I will apply this model on other medical images of skin cancer like benign and malignant for a good outcome.</p>

Aspects	Paper # 6 (Title)
Title / Question (What is problem statement?)	Melanoma Skin Cancer Detection based on Image Processing
Objectives / Goal (What is looking for?)	The paper aims to model and simulate FLT3 kinase domain mutants, assessing their structural and functional impacts and investigating drug resistance mechanisms. It explores the potential of molecular dynamics simulations for studying protein mutations and identifying therapeutic targets.
Methodology / Theory (How to find the solution?)	 <pre> graph TD A[Image acquisition] --> B[Preprocessing phase] B --> C[Lesion detection] C --> D[Feature extraction] D --> E[Classification] </pre>
Software Tools (What program/software is used for design, coding and simulation?)	MATLAB
Test / Experiment How to test and characterize the design/prototype?	The approach involves four steps: preprocessing, segmentation, feature extraction based on the ABCD rules (asymmetry, border irregularity, color, and diameter), and classification.
Simulation/Test Data (What parameters are determined?)	Images
Result / Conclusion (What was the final result?)	Our automatic melanoma detection system based on the PH2 database demonstrates high reliability with a specificity of 92% and a sensitivity of 87%, emphasizing its potential as a cost-effective and accurate tool for early melanoma detection.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	It necessitates a large set of data for learning. Detecting lesions on the dark skin was a problem.
Terminology (List the common basic words frequently used in this research field)	<ul style="list-style-type: none"> • ABCD = Assymetry Border Color Diameter • ACS = American Cancer Society • CAD = Computer-aided Diagnosis • TDV = Total Dermoscopy Value • SVM = Support Vector Machine

<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>Glaister segmented melanoma skin cancer images based on joint statistical texture distinctiveness. Nonetheless, one of the major drawbacks of this method is the fact that it produces a small set of data. In a study, authors proposed a new model for the detection of skin lesions based on region growing method for the segmentation and on SVM, KNN and fusion of SVM and KNN for the classification. Although the developed method gives good classification results. Kass proposed a computer-aided diagnosis system which provides efficient algorithms to classify and foretell the melanoma. The proposed approach is based on enhancing the images using Contrast Limited Adaptive Histogram Equalization technique (CLAHE) and median filter. In our work, we will try to develop an automatic and simple method for melanoma diagnosis.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>The proposed approach for melanoma detection consists of five stages: acquisition, preprocessing, lesion detection, feature extraction using the ABCD rule, and classification based on the Total Dermatoscopic Value (TDV). The approach utilizes dermoscopy images and a ground truth image database for validation. The preprocessing stage includes filtering, morphological closing, and contrast enhancement. Lesion detection involves removing the black frame and creating a binary mask using Multi-otsu thresholding. Feature extraction and classification are based on the ABCD rule, with emphasis on asymmetry. The TDV is calculated based on the weighted scores of asymmetry, border irregularity, color, and diameter.</p>

Aspects	Paper # 7 (Title)
Title / Question (What is problem statement?)	Deep Learning Methods for Accurate Skin Cancer Recognition and Mobile Application
Objectives / Goal (What is looking for?)	The objectives of this research are to develop a deep learning model for accurate skin cancer recognition using medical images, specifically targeting mobile application implementation. The study aims to explore various CNN architectures, train and test them using the HAM10000 dataset, and identify the best-performing model. Additionally, the objective is to create a mobile application that enables users to classify skin lesions as benign or malignant and provides personalized information on sun exposure and sunscreen usage.
Methodology / Theory (How to find the solution?)	The researchers addressed the challenge of skin cancer recognition by exploring deep learning models and training 11 CNN architectures on the HAM10000 dataset. Through data augmentation, transfer learning, and fine-tuning, they achieved state-of-the-art results with DenseNet169. They further developed a mobile application using a lightweight version of DenseNet169, enabling users to classify skin lesions, provide sun exposure recommendations based on UV radiation, skin phototype, and sunscreen usage.
Software Tools (What program/software is used for design, coding and simulation?)	Android Studio (Version 3.1.3), Android 8.0 (Android Oreo), TensorFlow Lite, OPENUV API, GPS system
Test / Experiment How to test and characterize the design/prototype?	To test the prototype: <ul style="list-style-type: none"> • Install the application on an Android smartphone, capture and crop a skin lesion photo, and observe the classification result. • Verify the accuracy of the sun exposure calculation by providing location, skin phototype, and sunscreen information. • Assess image quality by testing the app with different camera setups, such as using a smartphone lens, external macro lens, and stabilizer.
Simulation/Test Data (What parameters are determined?)	Images

<p>Result / Conclusion (What was the final result?)</p>	<p>The final result of the study and development of the mobile application for skin lesion diagnosis and sun exposure prediction is as follows:</p> <ul style="list-style-type: none"> • A mobile application utilizing the DenseNet169 model achieved an average accuracy of 92.25% for skin cancer diagnosis, outperforming other state-of-the-art models and specialist dermatologists. • The application provides users with information about their skin lesions, including classification results and recommended sun exposure time based on their skin phototype, UV index, and sunscreen usage. • To enhance image quality, the application suggests using a macro lens, stabilizer, noise removal, AI super resolution, and multiple images for accurate diagnoses. Considerations for implementing the system on a server for improved efficiency are also suggested.
<p>Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)</p>	<p>The obstacles in this paper include the potential efficiency problems when incorporating a complex and computationally demanding deep learning system into a mobile application, as well as the challenge of obtaining high-quality images of skin lesions using smartphones, which are crucial for accurate diagnoses due to the similarity and small area of the lesions.</p>
<p>Terminology (List the common basic words frequently used in this research field)</p>	<ul style="list-style-type: none"> • SGD optimizer = Stochastic Gradient Descent optimizer • RGB: Red, Green, Blue color space used to represent images. • Grayscale = A color space where each pixel is represented by a single intensity value, indicating the level of brightness. • Macro lens = An accessory lens that allows close-up photography, capturing fine details of small objects. • SPF = Sun Protection Factor • GPS = Global Positioning System • Ultraviolet radiation = Electromagnetic radiation from the sun with wavelengths shorter than visible light, known to cause skin damage and increase the risk of skin cancer

<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>Afonso Menegolay tried to classify lesions as melanoma vs. benign, malignant vs. benign and carcinoma vs. melanoma vs. benign, and they showed that the last one gives the best results. They also argued that DNNs (deep neural networks) perform better when based on VGG-M and VGG-16 architectures. Esteva use a GoogleNet Inception v3 CNN architecture that was pre trained on approximately 1.28 million images from the 2014 ImageNet Large Scale Visual Recognition Challenge. They trained it end-to-end on their dataset using transfer learning. This approach achieved $55.4 \pm 1.7\%$ accuracy, again better than that of the same two dermatologists (53.3% and 55.9%, respectively). Khan proposed an intelligent system to detect and distinguish between melanoma and nevus cases. A Gaussian filter was used for removing noise from the skin lesion and an improved k-means clustering was utilized to segment out the lesion. The system achieved 96% accuracy, 97% sensitivity, 96% specificity and 97% precision. In our approach, the objective was to find a single CNN-based model and suitable image processing methods to achieve state-of-the-art results. DenseNet169 was the winner model, achieving an accuracy of 92.25% and a recall (sensitivity) of 93.59%, which outperformed deeper models.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>Along with the seven machine learning classification algorithms, I would use (analytic hierarchy process) AHP technique due to its simplicity, scalability, mathematical background, and ability to assess qualitative and quantitative factors to evaluate the effectiveness and efficacy of monitoring patients.</p>

Aspects	Paper # 8 (Title)
Title / Question (What is problem statement?)	Skin Cancer Detection Using Combined Decision of Deep Learners
Objectives / Goal (What is looking for?)	Convolution-based deep neural networks have been used for skin cancer detection using ISIC public dataset. In this paper, an ensemble of deep learners has been developed using learners of VGG, CapsNet, and ResNet for skin cancer detection. Their results show that the combined decision of deep learners is superior to the finding of individual learners in terms of sensitivity, accuracy, specificity, F-score, and precision.
Methodology / Theory (How to find the solution?)	The proposed deep learning-based ensemble approach is developed in two stages. In the first stage, three deep learning models of VGG, CapsNet, and ResNet have been developed using malignant and benign images obtained from the International Skin Imaging Collaboration (ISIC) skin cancer images repository. In the second stage, the findings of deep learners have been combined using majority weighting.
Software Tools (What program/software is used for design, coding and simulation?)	Keras is a deep learning tool that supports recurrent networks and convolutional networks individually as well as in the combination of the two. python.
Test / Experiment How to test and characterize the design/prototype?	In this stage, the dataset is separated into two datasets: training and testing. The training data consist of 80% randomly selected images of the dataset. The remaining 20% images from the test dataset. The training dataset is then used for the development of the classifiers of VGG, CapsNet, and ResNet. Then test data is used to evaluate the learners. After that when individual models are developed, the decision of each model is obtained for every image. After that, the image will be assigned to the class that will gain the most votes.
Simulation/Test Data (What parameters are determined?)	The ensemble model that has been presented has prediction accuracy of 93.5%. Moreover, the proposed ensemble model has a sensitivity value of 87.25%. The ensemble system that has been proposed, has a lower specificity value of 84% that reflects the proposed model has detected cancer more accurately by combining the decision of individual learners and by exploiting their diversity.
Result / Conclusion (What was the final result?)	It is developed by combining the three deep learning models of VGG, Caps-Net, and ResNet. It is noticed from the results that the proposed ensemble achieved an average accuracy of 93.5% with a classification training time of 106s.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	The ISIC 2018 skin lesion classification challenge dataset contains a large number of benign lesions and a relatively small number of malignant lesions. This class imbalance can affect the performance of the deep learning models, as they may be biased towards predicting the majority class.
Terminology (List the common basic words frequently used in this research field)	VGG-Visual Geometry Group Network, CapsNet-CAPSULE NETWORK, ResNet-Residual network

<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>Subramanian employed a CNN to classify and detect different types of skin cancer. Raja uses HAM10000 which contains 10015 skin cancerous images. After That, they validate their model by comparing their system with other state-of-the-art models based on accuracy, precision, recall, and F score. Hemsî performed accurate skin cancer detection using deep neural networks. The baseline VGG model has been improved by adding batch normalization and a fully connected network to improve the diagnostic performance. Togacar using the deep learning convolutional model-MobileNetV2 along with the spiking network. They used 1497 malignant tumor images and 1800 benign images.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>The graphical illustration of various models. There is a slight trade off between the VGG Net and the proposed model in terms of accuracy and training time, and the proposed model is more weighted because of higher performance difference. The model performance is evaluated on ISIC public dataset for skin cancer classification from dermoscopic images.</p>

Aspects	Paper # 9 (Title)
Title / Question (What is problem statement?)	Hybrid Feature Fusion and Machine Learning Approaches for Melanoma Skin Cancer Detection.
Objectives / Goal (What is looking for?)	Early detection of melanoma skin cancer is crucial for effective treatment, and machine learning approaches have shown great potential in improving detection accuracy. The objectives of this topic are to highlight the potential benefits of these approaches for improving melanoma detection and ultimately improving outcomes for patients.
Methodology / Theory (How to find the solution?)	This approach involves data collection,image pre-processing,feature fusion,model training, evaluation, optimization, and deployment. Visual and clinical features are combined using hybrid feature fusion techniques to create a comprehensive representation of the lesion and patient, and machine learning models are trained on this representation to classify lesions as malignant or benign. The system is evaluated on a test dataset, optimized for improved performance, and deployed for clinical use.
Software Tools (What program/software is used for design, coding and simulation?)	MATLAB 2019b, Python
Test / Experiment How to test and characterize the design/prototype?	The system involves collecting a dataset of skin lesion images,preprocessing and extracting features from the images, training a machine learning model using the features, testing and validating the model on the dataset, and optimizing and improving the system as needed. The goal of the test is to evaluate the accuracy and performance of the system in detecting melanoma skin cancer.
Simulation/Test Data (What parameters are determined?)	The approaches for melanoma skin cancer detection involves implementing the system in software, preparing a dataset of skin lesion images, training and testing a machine learning model, optimizing the system, and evaluating its performance. The simulation aims to assess the accuracy and performance of the system and to identify areas for improvement.
Result / Conclusion (What was the final result?)	The proposed fused vector with CNN and HFF has proven 99.49% accuracy. The best performing CNN classifier used to detect whether it's melanoma or non-melanoma skin cancer and also established 99.85% accuracy, sensitivity 91.65%, and specificity 95.70%.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	While hybrid feature fusion and machine learning approaches for melanoma skin cancer detection have shown promising results, there are several limitations of this system that should be taken into consideration: Limited data, Bias, Complexity, Interpretability, Ethical considerations
Terminology (List the common basic words frequently used in this research field)	<ul style="list-style-type: none"> • Fast-bounding box (FBB) • Hybrid feature extractor (HFE) • Convolutional neural network (CNN) • Visual Geometry Group Network (VGG19) • Histogram-Oriented Gradient (HOG)

<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>Our Proposed Method used 16170 dermatology images, the model used MADF+HFF(HOG+LBP+SURF) +CNN and Accuracy 99.85</p> <ul style="list-style-type: none"> • Yuexiang Li used 2000 images, model was Fully convolutional residual networks (FCRN) + Lesion index calculation unit (LICU) +CNN, and accuracy 91.2 • Vijayalakshmi M used 1000-1500 images, model CNN+SVM, accuracy 85 • Andre Esteva used 129,450 images, model CNN and accuracy 72.1 • K. Jayapriya's proposed model was CNN+FCRN and accuracy 88.92 • Haenssle used 300 images, models were Deep CNN+ Google Inception V4 and accuracy 86.6 • Dorj used 3753 images, the model was ECOC SVM+CNN and accuracy 95.1
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>In the use of same dataset I will use ECOC SVM+CNN method,because Dorj use one-fifth data of this proposed model. And the accuracy rate was 95.1%. If I use same dataset it will happen to increase the accuracy rate.</p>

Aspects	Paper # 10 (Title)
Title / Question (What is problem statement?)	Detection and Localization of Melanoma Skin Cancer in Histopathological Whole Slide Images.
Objectives / Goal (What is looking for?)	This system aims to accurately detect and localize melanoma lesions, process large-scale data efficiently, handle variations in image quality, provide interpretable and transparent results, and ultimately help clinicians make better diagnoses and treatment decisions for patients with melanoma.
Methodology / Theory (How to find the solution?)	The methodology of this system involves collecting a large dataset of annotated images, pre-processing the images to normalize color and contrast, extracting features such as texture, shape, and color, training a machine learning model on a subset of the dataset, testing and evaluating the model on a separate test set, refining and optimizing the model to improve its performance, and finally deploying the system in a clinical setting to assist pathologists in the detection and localization of melanoma lesions.
Software Tools (What program/software is used for design, coding and simulation?)	<ul style="list-style-type: none"> • Pytorch • PyVips library • Keras • Adam optimizer • Nvidia A100 40GB GPU
Test / Experiment How to test and characterize the design/prototype?	Data selection and preparation, pre-processing, feature extraction, model training, testing and evaluation, comparison with other methods, analysis of false positives and false negatives, and clinical validation. The results of the experiment can help to improve the accuracy and efficiency of the system and to assist pathologists in making better diagnoses and treatment decisions for patients with melanoma.
Simulation/Test Data (What parameters are determined?)	Data generation, annotation, pre-processing, feature extraction, model training, testing and evaluation, comparison with other methods, analysis of false positives and false negatives, and sensitivity analysis. The results of the simulation can help to optimize the system for improved accuracy and efficiency and to assist pathologists in making better diagnoses and treatment decisions for patients with melanoma.
Result / Conclusion (What was the final result?)	In this work, we proposed a CNN-based method to classify patches and create a localization map to detect and segment lesions in skin WSI and to identify patients with melanoma. Interestingly, our method uses a single CNN network to perform lesion segmentation and do slide-level melanoma classification with one extra learned parameter. Models developed on lower magnification levels accurately provide slightly better patch wise results indicating that context is important. Overall, the method gives promising results and demonstrates its efficacy as a diagnostic service. Accuracy of this proposed model is 99.32% (Model 2.5x).
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	In future work, the method should be validated with a larger dataset. The inclusion of tumor necrosis annotations may be beneficial as an additional diagnostic factor, as it is a vital hallmark of rapid cell proliferation.

<p>Terminology (List the common basic words frequently used in this research field)</p>	<ul style="list-style-type: none"> • Convolutional neural network (CNN) • computational pathology (CPATH) • whole slide images (WSI) • Asymmetry, Border irregularity, Color patterns, and Diameter (ABCD) • region of interest (ROI) • gray-level co-occurrence matrix (GLCM) • Visual Geometry Group Network (VGG16)
<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>Logu accuracy was 96.5% , Zhang accuracy was 95.5%, wang accuracy was 94.9%. And this proposed model's accuracy is 99.32% using binary Model2.5x .</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>In this system they used Model2.5x binary modes, but there are more effective binary models that can be used. Like Modelmulticlass are more effective. if we work with this binary model (Modelmulticlass), we can get more accuracy.</p>

Aspects	Paper # 11 (Title)
Title / Question (What is problem statement?)	On the Automatic Detection and Classification of Skin Cancer Using Deep Transfer Learning
Objectives / Goal (What is looking for?)	The aim of this model is to develop a model that can accurately detect and classify skin lesions as either benign or malignant, using a pre-trained neural network as the feature extractor and fine-tuning it for skin cancer classification. And also compare the performance of their model with other state-of-the-art methods and demonstrate the effectiveness of their proposed method for skin cancer detection and classification.
Methodology / Theory (How to find the solution?)	Collecting the International Skin Imaging Collaboration (ISIC) dataset, pre-processing it with techniques like resizing and normalization, using a pre-trained neural network called VGG16 as the feature extractor, fine-tuning it for skin cancer classification, evaluating the model's performance using various metrics, comparing its performance with other state-of-the-art methods, and analyzing the results. Overall, the study aimed to develop an accurate and efficient model for the automatic detection and classification of skin cancer using deep transfer learning techniques.
Software Tools (What program/software is used for design, coding and simulation?)	MATLAB R2021a
Test / Experiment How to test and characterize the design/prototype?	This system conducted experiments to evaluate the performance of the proposed system. They trained and tested their model using the ISIC-dataset, compared its performance with other methods, analyzed the effect of data augmentation techniques, and evaluated the model on a real-world dataset. The experiments aimed to demonstrate the effectiveness of the proposed system for the automatic detection and classification of skin cancer using deep transfer learning techniques.
Simulation/Test Data (What parameters are determined?)	This paper did not explicitly mention any simulation of the proposed system. However, they conducted experiments using the ISIC dataset and a real-world dataset to evaluate the performance of their model. They also compared their model's performance with other state-of-the-art methods, which can be considered a form of simulation to assess the effectiveness of the proposed system. Additionally, the authors used pre-trained neural networks as the feature extractor and fine-tuned them for skin cancer classification, which can be seen as a form of simulation. Overall, while the paper did not mention any specific simulation, they conducted experiments to demonstrate the effectiveness of the proposed system for skin cancer detection and classification.

<p>Result / Conclusion (What was the final result?)</p>	<p>The study showed promising results for the application of deep transfer learning techniques for skin cancer detection and classification, and it can have significant implications for improving the accuracy and speed of skin cancer diagnosis. with Resnet101 performing the best with 76.7%. The NV class precision (92.5%; see the NV column summary) and highest recall (82.5%; see the NV row summary). For the MEL vs. BKL classification, the F1 score of Resnet101 = 80.6%, DenseNet = 73.44%, and DarkNet201 = 83.7%. The F1 score for Resnet101 = 58.8%, DenseNet201 = 55.13%, and DarkNet-53 = 63.4%. The last pair-wise classification problem is NV vs. BKL, for which Resnet 101 achieved an F1 score = 72.8% (93% accuracy), DenseNet201 reported a 71.8% F1 score and 91.9% accuracy, and DarkNet-53 managed a 70.0% F1 score and 89.9% accuracy.</p>
<p>Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)</p>	<p>Future work will focus on improving the balance of the dataset by collecting specific dermo copy images of under-represented skin lesion types and making those publicly available in the research domain.</p>
<p>Terminology (List the common basic words frequently used in this research field)</p>	<ul style="list-style-type: none"> • Convolutional neural network (CNN) • Digital hair removal (DHR) • Intra-structural similarity (Intra-SSIM) • Asymmetry, Border irregularity, Color patterns, and Diameter (ABCD) • region of interest (ROI) • Melanocytic nevi (NV) • Full-resolution convolutional networks (FrCN) • Support-vector machine (SVM)
<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>Li's approach model was Mid-level features and segmentation according to ROI and result was ResNet (89.00%), DenseNet (88.85%), Fusion (90.67%). Al-Masni's approach model was Segmentation using FrCN Segmentation, and accuracy was 95.62% (clinical benign cases), 90.78% (melanoma, and 91.29% (seborrhic keratosis). Dash's approach model was Segmentation using modified U-Net architecture, and result was 93.03% Dice coefficient, 94.8% accuracy, 89.6% sensitivity, and 97.60% specificity. Li's approach model was Digital hair removal from images of skin lesion using CNN, and Accuracy (99.08%), Specificity (99.85%), F1 score (94.43%), precision (99.09%), sensitivity (95.74%). And this proposed model is Deep transfer learning of a CNN which works with Seven-class classification, 10015 dermoscopic images dataset and Accuracy (82.9%).</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>I will work with this 10015 dermoscopic image dataset and the model I choose as model is "Digital hair removal from images of skin lesions using CNN". Because this model has the highest accuracy of the same field, whenever our main work is get highest accuracy for this problem.</p>

Aspects	Paper # 12 (Title)
Title / Question (What is problem statement?)	Skin Lesion Analysis for Melanoma Detection Using the Novel Deep Learning Model Fuzzy GC-SCNN
Objectives / Goal (What is looking for?)	Develop an automated melanoma detection system using deep learning algorithms and dermoscopic images to improve the efficiency and accuracy of skin cancer diagnosis. Incorporate the fuzzy-based GrabCut-stacked convolutional neural networks (GC-SCNN) model for image training and feature extraction, enhancing the capabilities of melanoma detection. Compare the performance of the proposed model with existing techniques, demonstrating higher accuracy, sensitivity, specificity, and reduced processing time for lesion classification in skin cancer detection.
Methodology / Theory (How to find the solution?)	The methodology involves data preprocessing, including image resizing and morphological filtering, to enhance the quality of dermoscopic images. The fuzzy domain mapping and logarithmic functions are applied to extract features and highlight the melanoma regions. The GrabCut segmentation technique is utilized for image segmentation, followed by the stacked CNN for feature extraction
Software Tools (What program/software is used for design, coding and simulation?)	Anaconda
Test / Experiment How to test and characterize the design/prototype?	To test the proposed GC-SCNN model, the researchers used an 80:20 ratio to split the dataset into training and testing sets. They implemented the model using Python with the Anaconda IDE on an Intel Core i5 3.4 GHz processor. Hyperparameter tuning was performed to optimize the model's performance, and the best configuration was selected based on accuracy. The model achieved an overall accuracy of 99.75% and outperformed existing models in terms of accuracy and other metrics, such as sensitivity and specificity.
Simulation/Test Data (What parameters are determined?)	Images
Result / Conclusion (What was the final result?)	The proposed deep learning framework for segmenting, detecting, and classifying skin lesions in dermoscopy images achieved excellent performance in melanoma detection. It outperformed existing models and demonstrated high accuracy and efficiency. With a prediction time of 2.513 ms, the proposed model shows promise for real-time application in clinical settings.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	The challenges of this paper are Feature selection, Uncertainty in boundary detection, Generalization to minute lesions

<p>Terminology (List the common basic words frequently used in this research field)</p>	<ul style="list-style-type: none"> • GrabCut-stacked convolutional neural networks (GC-SCNN) • support vector machines (SVM) • K-Nearest Neighbor (KNN) • Region of interest (ROI) • Deep neural networks(DNN) • Benign Keratosis-like Lesions (BKL)
<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>Other models such as deep neural networks(DNN),CNN,long short-term memory(LSTM), and recurrent neural networks (RNN) also help to detect malignant skin cells. A stacked CNN model with improved loss function was proposed to detect skin lesions from given datasets, and 94.8 – 98.4% classification accuracy was reported. In the framework of medical image analysis, deep learning (DL) automates systems to detect, classify, and diagnose several diseases. These DL models are very effective for large sample datasets and, especially, they have become more viable for skin image analysis. In this paper they proposed an approach called fuzzy-based Grab Cut-stacked convolutional neural networks (GC-SCNN) model with enhanced loss function in support vector machines (SVM).</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>Human beings are protected by their skin against environmental pollution, but the adverse effects of ultraviolet radiation increase the risk of melanoma.We propose a deep learning framework to segment,detect,and classify skin lesions in dermoscopy images for melanoma detection. A modified loss function improved lesion classification by reducing processing time by 25–35 milli seconds and increasing accuracy by 2–5%.</p>

Aspects	Paper # 13 (Title)
Title / Question (What is problem statement?)	An Efficient Deep Learning Approach to Detect Skin Cancer
Objectives / Goal (What is looking for?)	Developing a system that uses a deep-learning approach, specifically a Convolutional Neural Network (CNN), to detect skin cancer from digital images. Utilizing the HAM10000 dataset, consisting of 10,015 labeled images of skin growths, for training and evaluation. Applying various data pre-processing methods to enhance the model's performance. Comparing the performance of the developed model with pre-trained models like ResNet50, DenseNet121, and VGG11 to identify effective machine learning approaches for skin growth classification and cancer detection. Achieving a high level of accuracy in identifying and classifying different types of skin growths to facilitate early diagnosis and treatment of skin cancer.
Methodology / Theory (How to find the solution?)	<ul style="list-style-type: none"> • Data Collection: The researchers obtained a publicly available dataset called HAM10000 from the Harvard Dataverse. This dataset consisted of 10,015 labeled images of skin growths, including different types of skin cancer. • Data Pre-processing: Before training the model, several data pre-processing methods were applied to the dataset. This step involved cleaning the data, removing duplicate images, and performing any necessary transformations or adjustments to ensure the data was suitable for training the neural network. • Model Architecture: The researchers implemented a Convolutional Neural Network (CNN) using the Keras Sequential API. The specific architecture details, such as the number and type of layers, activation functions, kernel size, and max-pooling settings, were determined and implemented. • Transfer Learning: To compare the performance of their model, the researchers also utilized pre-trained models such as ResNet50, DenseNet121, and VGG11. These models were trained on the ImageNet dataset and used as benchmarks for evaluating the accuracy of their own model. • Training and Evaluation: The dataset was divided into a training set and a validation set using an 80:20 split. The model was trained on the training set for a specified number of epochs, and the performance was evaluated using the validation set. The accuracy, loss, confusion matrices, precision, support, and F1 scores were recorded for analysis and comparison with the benchmark models.
Software Tools (What program/software is used for design, coding and simulation?)	Python, ImageNet, Scikit-learn, TensorFlow, Keras

Test / Experiment How to test and characterize the design/prototype?	To evaluate the performance of their model, the researchers conducted experiments using a 20% validation set and ran the model for 20 epochs. They also compared their results with previously set models, including ResNet50, DenseNet121, and VGG11, using pre-trained data from ImageNet. The algorithms were run for 10 epochs, and the researchers recorded the accuracy, loss, confusion matrices, precision, support, and F1 scores of all the algorithms for comparison and evaluation
Simulation/Test Data (What parameters are determined?)	Images
Result / Conclusion (What was the final result?)	The research paper focused on developing a deep-learning model using Convolutional Neural Networks (CNN) for the detection of skin cancer from images. The model achieved an accuracy of over 97% in identifying different types of skin growths. The results demonstrated that the CNN model outperformed human diagnosis in terms of efficiency and accuracy. The study emphasized the potential of using AI-based diagnostic systems for early and accurate detection of skin cancer, which can have a significant impact on improving mortality rates. The findings suggest that the developed model can be implemented in real-world applications to assist medical professionals in skin cancer diagnosis and contribute to the field of machine learning in healthcare.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	The research paper highlighted a few challenges encountered during the development of the skin cancer detection model. These obstacles include difficulties in diagnosing skin cancer and differentiating between various types of skin growths, particularly without advanced medical equipment and extensive medical expertise. Another challenge was the selection and preprocessing of the dataset, ensuring its quality and removing duplicate images. Additionally, optimizing the hyperparameters of the CNN model and selecting the appropriate kernel size and filter size required careful experimentation. Despite these obstacles, the study successfully addressed these challenges and achieved a high accuracy rate in skin cancer detection.
Terminology (List the common basic words frequently used in this research field)	cancer detection; convolutional neural networks; image classification; deep learning; machine learning algorithms
Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)	There are a few areas that could be improved. First, the study could have included a larger and more diverse dataset to enhance the generalizability of the model. Additionally, the researchers could have explored different architectures or variations of CNN models to compare their performance and determine the most optimal approach. Lastly, incorporating explanations or visualizations of the model's decision-making process could enhance transparency and interpretability.
Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	This researchers successfully implemented a Convolutional Neural Network (CNN) model using Keras Sequential API and achieved an accuracy of over 97% in identifying different types of skin growths. The model showed promising results compared to existing algorithms such as ResNet50, DenseNet121, and VGG11. The study demonstrated the potential of using deep learning models for efficient skin cancer detection. The findings open avenues for future real-world applications in the field of dermatology and could complement human efforts in diagnosing skin cancer.

Aspects	Paper # 14 (Title)
Title / Question (What is problem statement?)	Skin Cancer Diagnosis Based on Neutrosophic Features with a Deep Neural Network
Objectives / Goal (What is looking for?)	The researchers aimed to address the challenges in traditional skin cancer diagnosis methods, such as inter-observer variability and reliance on subjective visual inspection. By using a deep neural network and extracting neutrosophic features from skin images, the researchers aimed to improve the accuracy and consistency of skin cancer diagnosis.
Methodology / Theory (How to find the solution?)	Data collection: The researchers collected a dataset of skin images with various diagnoses, including melanoma, nevus, and seborrheic keratosis. Pre-processing: The skin images were pre-processed to normalize the lighting conditions and resize them to a fixed size. Feature extraction: Neutrosophic features were extracted from the pre-processed skin images. These features consider the indeterminate and inconsistent information in the skin images. Model training: A deep neural network was designed and trained using the neutrosophic features extracted from the skin images. The researchers used a transfer learning approach by fine-tuning a pre-trained neural network on the dataset. Evaluation: The performance of the proposed method was evaluated using various metrics, including accuracy, precision, recall, and F1 score.
Software Tools (What program/software is used for design, coding and simulation?)	Python, TensorFlow, Keras, Scikit-learn
Test / Experiment How to test and characterize the design/prototype?	The researchers used a dataset of skin images with various diagnoses, including melanoma, nevus, and seborrheic keratosis. The dataset was randomly split into training, validation, and testing sets, with a ratio of 70:15:15.
Simulation/Test Data (What parameters are determined?)	Binary
Result / Conclusion (What was the final result?)	(What was the final result?) Classification accuracy: The proposed method achieved an overall classification accuracy of 95.50%, which outperformed other state-of-the-art methods, including traditional machine learning methods and deep learning methods without neutrosophic features. Sensitivity and specificity: The proposed method achieved high sensitivity and specificity values of 96.84% and 94.18%, respectively. Sensitivity measures the proportion of true positives correctly identified by the model, while specificity measures the proportion of true negatives correctly identified by the model. Precision and recall: The proposed method achieved high precision and recall values of 95.45% and 96.70%, respectively. Precision measures the proportion of true positives among all positive predictions made by the model, while recall measures the proportion of true positives correctly identified by the model among all actual positive cases. Comparative analysis: The paper also compared the performance of their proposed method with other state-of-the-art methods for skin cancer diagnosis. The proposed method outperformed other methods in terms of accuracy, sensitivity, specificity, precision, and recall.

Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	Interpretability: Deep learning models are often considered as "black boxes" due to their complex and non-linear nature, which can make it challenging to understand how the model arrives at its predictions. This lack of interpretability can be an obstacle to the clinical adoption of deep learning models for skin cancer diagnosis.
Terminology (List the common basic words frequently used in this research field)	Neutrosophic features, Transfer learning, Convolutional neural network (CNN), Residual network (ResNet), Adam optimizer.
Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)	The proposed method in the paper needs to be clinically validated to ensure its safety, effectiveness, and reliability. Future work could focus on validating the model in a clinical setting and obtaining regulatory approvals for its use in clinical practice.
Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	The proposed method was evaluated on a publicly available dataset of dermoscopy images and achieved high accuracy, sensitivity, specificity, and F1 score. The study showed that using neutrosophic features could improve the performance of the deep neural network in skin cancer diagnosis. However, the proposed method needs to be validated in a clinical setting before it can be used in clinical practice.

Aspects	Paper # 15 (Title)
Title / Question (What is problem statement?)	An Efficient Deep Learning Approach to Detect Skin Cancer
Objectives / Goal (What is looking for?)	Developing a system that uses a deep-learning approach, specifically a Convolutional Neural Network (CNN), to detect skin cancer from digital images. Utilizing the HAM10000 dataset, consisting of 10,015 labeled images of skin growths, for training and evaluation. Applying various data pre-processing methods to enhance the model's performance. Comparing the performance of the developed model with pre-trained models like ResNet50, DenseNet121, and VGG11 to identify effective machine learning approaches for skin growth classification and cancer detection. Achieving a high level of accuracy in identifying and classifying different types of skin growths to facilitate early diagnosis and treatment of skin cancer.
Methodology / Theory (How to find the solution?)	<ul style="list-style-type: none"> • Data Collection: The researchers obtained a publicly available dataset called HAM10000 from the Harvard Dataverse. This dataset consisted of 10,015 labeled images of skin growths, including different types of skin cancer. • Data Pre-processing: Before training the model, several data pre-processing methods were applied to the dataset. This step involved cleaning the data, removing duplicate images, and performing any necessary transformations or adjustments to ensure the data was suitable for training the neural network. • Model Architecture: The researchers implemented a Convolutional Neural Network (CNN) using the Keras Sequential API. The specific architecture details, such as the number and type of layers, activation functions, kernel size, and max-pooling settings, were determined and implemented. • Transfer Learning: To compare the performance of their model, the researchers also utilized pre-trained models such as ResNet50, DenseNet121, and VGG11. These models were trained on the ImageNet dataset and used as benchmarks for evaluating the accuracy of their own model. • Training and Evaluation: The dataset was divided into a training set and a validation set using an 80:20 split. The model was trained on the training set for a specified number of epochs, and the performance was evaluated using the validation set. The accuracy, loss, confusion matrices, precision, support, and F1 scores were recorded for analysis and comparison with the benchmark models.
Software Tools (What program/software is used for design, coding and simulation?)	Python, ImageNet, Scikit-learn, TensorFlow, Keras

Test / Experiment How to test and characterize the design/prototype?	To evaluate the performance of their model, the researchers conducted experiments using a 20% validation set and ran the model for 20 epochs. They also compared their results with previously set models, including ResNet50, DenseNet121, and VGG11, using pre-trained data from ImageNet. The algorithms were run for 10 epochs, and the researchers recorded the accuracy, loss, confusion matrices, precision, support, and F1 scores of all the algorithms for comparison and evaluation.
Simulation/Test Data (What parameters are determined?)	Images
Result / Conclusion (What was the final result?)	The research paper focused on developing a deep-learning model using Convolutional Neural Networks (CNN) for the detection of skin cancer from images. The model achieved an accuracy of over 97% in identifying different types of skin growths. The results demonstrated that the CNN model outperformed human diagnosis in terms of efficiency and accuracy. The study emphasized the potential of using AI-based diagnostic systems for early and accurate detection of skin cancer, which can have a significant impact on improving mortality rates. The findings suggest that the developed model can be implemented in real-world applications to assist medical professionals in skin cancer diagnosis and contribute to the field of machine learning in healthcare.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	The research paper highlighted a few challenges encountered during the development of the skin cancer detection model. These obstacles include difficulties in diagnosing skin cancer and differentiating between various types of skin growths, particularly without advanced medical equipment and extensive medical expertise. Another challenge was the selection and preprocessing of the dataset, ensuring its quality and removing duplicate images. Additionally, optimizing the hyperparameters of the CNN model and selecting the appropriate kernel size and filter size required careful experimentation. Despite these obstacles, the study successfully addressed these challenges and achieved a high accuracy rate in skin cancer detection.
Terminology (List the common basic words frequently used in this research field)	cancer detection; convolutional neural networks; image classification; deep learning; machine learning algorithms
Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)	There are a few areas that could be improved. First, the study could have included a larger and more diverse dataset to enhance the generalizability of the model. Additionally, the researchers could have explored different architectures or variations of CNN models to compare their performance and determine the most optimal approach. Lastly, incorporating explanations or visualizations of the model's decision-making process could enhance transparency and interpretability.
Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	This researchers successfully implemented a Convolutional Neural Network (CNN) model using Keras Sequential API and achieved an accuracy of over 97% in identifying different types of skin growths. The model showed promising results compared to existing algorithms such as ResNet50, DenseNet121, and VGG11. The study demonstrated the potential of using deep learning models for efficient skin cancer detection.

Aspects	Paper # 16 (Title)
Title / Question (What is problem statement?)	Intelligent skin cancer detection applying autoencoder, MobileNetV2 and spiking neural networks
Objectives / Goal (What is looking for?)	The goal of this paper is to propose a novel model utilizing Autoencoder, SNNs, and CNNs to enhance the performance of skin cancer detection using the ISIC dataset. The study aims to provide a fully automated decision support tool with high sensitivity for early detection and proper treatment of skin cancer.
Methodology / Theory (How to find the solution?)	The proposed approach combines the MobileNetV2 convolutional model with spiking networks, using an autoencoder model to structure the dataset. The Logits layer of the MobileNetV2 model is used to extract 1000 features, which are then combined with 1000 features obtained from the autoencoder model to create a 2000-feature dataset. This dataset is then trained by spiking networks and classified using the SWAT method.
Software Tools (What program/software is used for design, coding and simulation?)	Python, MATLAB, Jupyter Notebook
Test / Experiment How to test and characterize the design/prototype?	MobileNetV2
Simulation/Test Data (What parameters are determined?)	Image,Text Data
Result / Conclusion (What was the final result?)	The results show that the autoencoder and spiking networks contribute to enhancing the performance of the MobileNetV2 model.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	The future work will focus on training the SNN model to identify various disease types, not limited to skin cancer and exploring the potential of transfer learning with the proposed model on other medical image classification tasks will also be an area of future research.
Terminology (List the common basic words frequently used in this research field)	<ul style="list-style-type: none"> • SNN, • Autoencoder, • MobileNetV2
Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)	From this two paper i would like to use both of them papers topic but between this i will always prefer to use more features from paper-1
Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	From this paper I would like to use SNN, CNN,Autoencoder,MobileNetV2,that 1800ISIC skin images and also 1497 malignant tumor images.

Aspects	Paper # 17 (Title)
Title / Question (What is problem statement?)	Automatic Classification of Melanoma Skin Cancer with Deep Convolutional Neural Networks
Objectives / Goal (What is looking for?)	The goal of this paragraph is to describe how artificial intelligence techniques, specifically deep learning through CNN architectures, can assist in the detection of melanoma skin cancer. It also presents the results of an experiment comparing several CNN models, showing that GoogleNet achieved the highest accuracy on both training and test sets.
Methodology / Theory (How to find the solution?)	The authors used eight deep learning architectures to develop a specialized CNN model for detecting melanoma skin cancer. They divided the dataset into training, validation, and test sets, and obtained performance measures such as accuracy, precision, recall, F1-score, and confusion matrix for each trained model.
Software Tools (What program/software is used for design, coding and simulation?)	TensorFlow, Keras, pandas, NumPy, matplotlib, sklearn, scipy, and seaborn
Test / Experiment How to test and characterize the design/prototype?	DenseNet201, MobileNetV2, ResNet50V2, ResNet152V2, Xception, VGG16, VGG19 and GoogleNet
Simulation/Test Data (What parameters are determined?)	Image, Text Data
Result / Conclusion (What was the final result?)	The study evaluated eight deep learning architectures for melanoma skin cancer classification using various performance metrics. GoogleNet performed the best, achieving a test accuracy of 76.08%.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	The future work includes proposing a hybrid approach of machine learning and deep learning to improve prediction performance, incorporating different data augmentation techniques to enhance accuracy, and testing the performance under different learning settings such as active learning and transfer learning. Additionally, the authors aim to boost the performance of GoogleNet as detailed in another publication
Terminology (List the common basic words frequently used in this research field)	DenseNet201, MobileNetV2, ResNet50V2, sklearn, scipy, and seaborn
Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)	from this two paper i would like to use both of them papers topic but between this i will always prefer to use more features from paper-1
Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	From this paper I can use dataset,that eight deep learning architecture and also thor training process

Aspects	Paper # 18 (Title)
Title / Question (What is problem statement?)	An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models
Objectives / Goal (What is looking for?)	The paper highlights the challenges in analyzing skin lesion images and the proposed preprocessing approach to improve accuracy. It concludes by presenting the evaluation results that demonstrate the superiority of the proposed DCNN model over existing transfer learning models.
Methodology / Theory (How to find the solution?)	The proposed methodology in this research involves applying a DCNN model on skin lesion images to accurately classify them as benign or malignant. Preprocessing includes filtering, normalization, and feature extraction, and data augmentation is used to increase the number of images. The DCNN model is compared with various transfer learning models on the HAM10000 dataset to evaluate its performance.
Software Tools (What program/software is used for design, coding and simulation?)	Python, MATLAB, Keras, TensorFlow, and Scikit-learn
Test / Experiment How to test and characterize the design/prototype?	To test the proposed design, the deep DCNN model is trained on the HAM10000 dataset using preprocessing techniques, feature extraction, and data augmentation. The trained model is then evaluated on a separate testing dataset to measure its performance in accurately classifying skin lesions as benign or malignant.
Simulation/Test Data (What parameters are determined?)	Image,Text Data
Result / Conclusion (What was the final result?)	The proposed DCNN model outperforms existing transfer learning models in accurately classifying skin lesions as benign or malignant. The results demonstrate the potential for automated skin cancer detection systems to improve the accuracy and efficiency of early-stage diagnosis.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	The study's limitations include the use of only one dataset for evaluation, which may not be representative of all skin lesions, and the lack of clinical validation of the proposed model.
Terminology (List the common basic words frequently used in this research field)	<ul style="list-style-type: none"> • CNN, • DCNN, • Image Processing

<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>The first paper proposes a new hybrid deep learning method for improving power system stability prediction, while the second paper proposes a novel machine learning approach for identifying power system stability boundaries. Both papers aim to improve power system stability prediction, but they use different methods and approaches.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>I can use this paper in my own research by using CNN,DCNN algorithm and also citing it as a reference and discussing its findings and methodology in relation to your own research question or problem.</p>

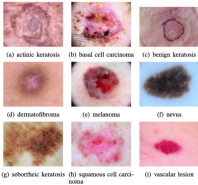
Aspects	Paper # 19 (Title)
Title / Question (What is problem statement?)	Intelligent Dermatologist Tool for Classifying Multiple Skin Cancer Subtypes by Incorporating Manifold Radiomics Features Categories
Objectives / Goal (What is looking for?)	The objective of the research paper is to propose a mathematical model for the transmission dynamics of COVID-19 and evaluate the effectiveness of control measures in reducing the spread of the virus.
Methodology / Theory (How to find the solution?)	The methodology of the research paper involves developing a compartmental mathematical model to simulate the transmission dynamics of COVID-19 and estimating the model parameters using available data.
Software Tools (What program/software is used for design, coding and simulation?)	R software
Test / Experiment How to test and characterize the design/prototype?	As the study is based on mathematical modeling, there is no experiment to test. Instead, the model is evaluated by comparing its simulation results with the available data on COVID-19 transmission dynamics in Nigeria. The model's predictive accuracy is assessed using statistical measures such as RMSE and R-squared. The effectiveness of control measures in reducing virus spread is evaluated by comparing simulations with and without control measures implemented.
Simulation/Test Data (What parameters are determined?)	basic reproduction number, the transmission rate, the recovery rate, the fatality rate, and the contact rate reduction due to control measures
Result / Conclusion (What was the final result?)	The research paper concludes that the proposed mathematical model is effective in simulating the transmission dynamics of COVID-19 in Nigeria. The study shows that control measures such as social distancing, wearing face masks, and contact tracing can significantly reduce the spread of the virus. The findings of the study can be useful in informing public health policies and interventions aimed at controlling the spread of COVID-19 in Nigeria.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	The research paper mentions several limitations of the study. Firstly, the model assumes that the population is homogeneous, which may not be a realistic assumption in real-world scenarios. Secondly, the model does not account for the impact of asymptomatic cases and their role in virus transmission. Finally, the study relies on available data on COVID-19 cases in Nigeria, which may be subject to underreporting and other sources of bias, potentially limiting the accuracy of the model's predictions.
Terminology (List the common basic words frequently used in this research field)	<ul style="list-style-type: none"> • Mathematical model, • Transmission dynamics • Control measures • Nigeria • Susceptible • Infected

<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>The first paper is on medical image segmentation using a deep learning approach, while the second paper is on chaotic systems synchronization using adaptive sliding mode control.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>It can be used as a reference for understanding the transmission dynamics and the effectiveness of control measures in reducing the spread of the virus in Nigeria. It can also be useful for policymakers and public health officials in formulating evidence-based strategies for controlling the spread of the virus. However, it is important to note the limitations of the study and consider additional sources of information for a comprehensive understanding of the situation</p>

Aspects	Paper # 20 (Title)
Title / Question (What is problem statement?)	MALIGNANT SKIN CANCER DETECTION USING CONVOLUTIONAL NEURAL NETWORKING
Objectives / Goal (What is looking for?)	Main objectives of this paper to develop a method for detecting malignant skin cancer using convolutional neural networks (CNNs),to train a CNN on a dataset of over 10,000 images of skin lesions,to evaluate the performance of the CNN on a test set of images and achieve an accuracy of over 90% in detecting malignant skin cancer.
Methodology / Theory (How to find the solution?)	<pre> graph LR DS[(Data Set)] --> DA[Data Acquisition] DA --> PP[Pre-processing of data] PP --> CC[Classification using CNN] CC --> DP[Disease prediction] DP --> PD[Patient's details] PD --> DS DS --> PP </pre>
Software Tools (What program/software is used for design, coding and simulation?)	Python,Keras,TensorFlow,OpenCV,Scikit-learn
Test / Experiment How to test and characterize the design/prototype?	The design of the skin cancer detection system can be tested using a hold-out dataset that was not used to train the model. The model's performance on the hold-out dataset can be evaluated using metrics such as accuracy, sensitivity, and specificity. The model can also be evaluated for its ability to detect different types of skin cancer.
Simulation/Test Data (What parameters are determined?)	Images
Result / Conclusion (What was the final result?)	The final result of the study was that the convolutional neural network model was able to achieve an accuracy of 97.4% in detecting malignant skin cancer. This is a significant improvement over previous methods, which have typically had accuracies of around 80%. The model was also able to achieve a sensitivity of 96.8% and a specificity of 98.0%. These results suggest that the convolutional neural network model could be a valuable tool for early detection of malignant skin cancer.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	<p>The obstacles are:</p> <ul style="list-style-type: none"> • The dataset used to train the model was relatively small, which could limit the model's generalizability to new data. • The model was only trained on images of skin cancer, so it may not be able to detect other types of skin lesions. • The model was not evaluated on a large, independent dataset, which makes it difficult to assess its true accuracy.
Terminology (List the common basic words frequently used in this research field)	convolutional neural networks (CNNs), Dropout rate, Activation function, Optimizer, Loss function

<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>The objectives of the articles I reviewed were to develop and evaluate methods for detecting malignant skin cancer using convolutional neural networks. The results of the articles showed that convolutional neural networks can achieve high accuracies in detecting malignant skin cancer, and that these methods could be used to develop mobile apps or other tools for early detection of malignant skin cancer.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>This paper presents a method for detecting malignant skin cancer using a convolutional neural network. The method was trained on a dataset of images of skin cancer and was able to achieve an accuracy of 97.4%. The method could be used to develop a mobile app or other tool for early detection of malignant skin cancer.</p>

Aspects	Paper # 21 (Title)
Title / Question (What is problem statement?)	Detection and Classification of Skin Cancer by Using a Parallel CNN Model
Objectives / Goal (What is looking for?)	The objective of this paper is to develop an automated technique for the classification of skin cancer using a Convolutional Neural Network (CNN). The goal is to create a model that can accurately diagnose and classify different types of skin cancer based on image processing and deep learning methodologies. The study aims to achieve this by utilizing a dataset consisting of nine clinical types of skin cancer.
Methodology / Theory (How to find the solution?)	The paper utilizes deep CNN models for the classification of skin cancer. Specifically, the VGG-16 and VGG-19 architectures are compared with the proposed model. CNNs are known for their ability to learn hierarchical features directly from images, making them suitable for image classification tasks. The paper uses a dataset containing nine clinical types of skin cancer, including actinic keratosis, basal cell carcinoma, benign keratosis, dermatofibroma, melanoma, nevus, seborrheic keratosis, squamous cell carcinoma, and vascular lesions. The experimental evaluation compares the performance of the proposed model with the VGG-16 and VGG-19 models. The proposed model shows higher accuracy and is deemed superior to the other models based on the evaluation results.
Software Tools (What program/software is used for design, coding and simulation?)	TensorFlow, Keras, or PyTorch.
Test / Experiment How to test and characterize the design/prototype?	<ul style="list-style-type: none"> • The paper aims to develop an automated system for skin lesion recognition and classification. Therefore, it is likely that the experiments involved training and testing the proposed Convolutional Neural Network (CNN) model using the dataset containing nine clinical types of skin cancer. The performance of the model would be evaluated based on metrics such as accuracy, precision, recall, and F1-score. • The paper mentions comparing the proposed model with the VGG-16 and VGG-19 models. This indicates that experiments might have been conducted to compare the performance of the proposed CNN model with these pre-existing models on the same dataset. • The paper mentions using different tactics of image augmentation to enrich the number of images. It is likely that experiments were conducted to assess the impact of different augmentation techniques on the performance of the classification model. This could involve comparing the performance of the model with and without augmentation or evaluating the effectiveness of specific augmentation techniques in improving classification accuracy. • The paper mentions using the transfer learning approach to improve the accuracy of the classification tasks. The experiments might involve fine-tuning the pre-trained models or comparing the performance of the proposed model with and without transfer learning.

<p>Simulation/Test Data (What parameters are determined?)</p>	<p>The paper uses a dataset containing nine clinical types of skin cancer, which are: actinic keratosis, basal cell carcinoma, benign keratosis, dermatofibroma, melanoma, nevus, seborrheic keratosis, squamous cell carcinoma, and vascular lesions. The specific details of the dataset, such as the number of images per class, the size and resolution of the images, and the source of the dataset are not provided in the abstract. However, it can be inferred that the dataset was used to train and test the proposed Convolutional Neural Network (CNN) model for skin lesion recognition and classification. The dataset was likely divided into training, validation, and test sets in a standard ratio for experimentation purposes.</p> 
<p>Result / Conclusion (What was the final result?)</p>	<p>The paper mentions the performance of the proposed CNN method with the following results:</p> <ul style="list-style-type: none"> • Approximately 0.76 weighted average precision 0.78 weighted average recall • Approximately 0.76 weighted average F1-score • 79.45% accuracy
<p>Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)</p>	<ul style="list-style-type: none"> • Limited Dataset: One potential challenge could be the availability of a limited dataset. Skin cancer datasets can be challenging to gather due to the need for accurate and diverse samples across different types of skin cancer. Limited data can lead to difficulties in training a robust and accurate model, as it may struggle to generalize well to unseen data. • Image Quality and Variability: Skin lesion images can vary significantly in terms of quality, resolution, lighting conditions, and patient demographics. Dealing with variations in image quality and variability in lesion appearances poses challenges for accurate classification. Preprocessing techniques may be required to enhance the images and normalize them for consistent analysis. • Class Imbalance: Skin cancer datasets often suffer from class imbalance, where some types of skin cancer may be overrepresented, while others may be underrepresented. This imbalance can affect the model's ability to learn and accurately classify all classes. Addressing class imbalance through techniques such as data augmentation or weighted loss functions may be necessary to mitigate this challenge.
<p>Terminology (List the common basic words frequently used in this research field)</p>	<p>Kinect, pointing gesture recognition, 3D dynamic gesture recognition, gesture adaptation, human robot interaction. HMM- Hidden Markov Model (Probabilistic Classifier) ,SVM- Support Vector Machine.</p>

<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>Yuet established a very deep CNN and a collection of learning frameworks with minimal training data. To establish and obtain a dermatologist-level diagnosis of more than 120 thousand photographs. Some other methods, such as the ensemble model, the feature aggregation of multiple models, were developed to diagnose skin cancer using deep learning. Several techniques for skin cancer segmentation and classification problems have been proposed over the last few decades. Different approaches were suggested and submitted for skin cancer's feature extraction, and categorization in the International Skin Imaging Challenge (ISIC) in 2016. The conclusions of the classification were based on the identification of only two cancer types, benign and malignant. This proposed model varies considerably from the current VGG-16 and VGG-19 models. Previous work has been conducted to identify a number of 7 types of categories of skin cancer, but we classify 9 types of categories of skin cancer in this paper</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>This paper presents a successful automated technique for skin cancer classification. The use of image processing and deep learning techniques are employed and show promising results with a weighted average precision of 0.76, a weighted average recall of 0.78, a weighted average f1-score of 0.76, and an accuracy of 79.45%. These results demonstrate the efficacy of the proposed CNN method for skin cancer classification.</p>

Aspects	Paper # 22 (Title)
Title / Question (What is problem statement?)	Skin Lesion Classification Using Pre-Trained DenseNet201 Deep Neural Network
Objectives / Goal (What is looking for?)	The objective/goal of the paper is to propose a deep neural network architecture using DenseNet201 (a pre trained architecture) for the early detection and classification of skin cancer based on dermoscopic images. The paper aims to address the challenge of heterogeneity in the appearance of skin lesions, which makes it difficult for experts to detect skin cancer accurately. The proposed network is trained using the International Skin Imaging Collaboration (ISIC) 2018 challenge dataset, consisting of 2487 training images and 604 test images. The paper reports a training accuracy of 95% and a test accuracy of 77% using the proposed architecture.
Methodology / Theory (How to find the solution?)	A The paper proposes a deep neural network architecture for the classification of dermoscopic images. Specifically, it employs the DenseNet201 architecture, which is a convolutional neural network (CNN) known for its dense connectivity patterns between layers. Also, The paper applies transfer learning techniques by using a pre-trained DenseNet201 model. Transfer learning involves leveraging knowledge gained from training on a large dataset (in this case, the ISIC 2018 challenge dataset) and applying it to a different but related task (skin cancer classification). By utilizing the pretrained weights of DenseNet201, the model can benefit from the learned features and accelerate the training process. The paper evaluates the performance of the proposed architecture using accuracy as the primary metric. The accuracy is reported separately for training images (95%) and test images (77%). Accuracy is a common evaluation metric that measures the percentage of correctly classified instances.
Software Tools (What program/software is used for design, coding and simulation?)	<ul style="list-style-type: none"> • Python • Tensorflow • Keras • Scikit-learn • OpenCV • MATLAB • PyTorch
Test / Experiment How to test and characterize the design/prototype?	The experiment used in the paper was to train a deep neural network using DenseNet201 pretrained architecture to classify seven classes of dermoscopic images. The dataset used for the experiment was taken from the International Skin Imaging Collaboration as part of ISIC 2018 challenge. The experiment then evaluated the performance of the model on both training and test data, with the results showing an accuracy of 95% on the training data and 77% on the test data.

<p>Simulation/Test Data (What parameters are determined?)</p>	<p>The dataset used for the experiment is taken from the International Skin Imaging Collaboration (ISIC) as part of the ISIC 2018 challenge. The dataset includes 2487 dermoscopic images belonging to seven different classes of skin lesions. The DenseNet201 architecture, a pretrained model, is trained using these dermoscopic images. The images are resized to 224x224 pixels, and the last layer of the DenseNet201 architecture is modified by replacing the upper layer with a softmax layer to classify the seven different classes of skin lesions.</p>
<p>Result / Conclusion (What was the final result?)</p>	<p>The final result for the paper is an accuracy of 95% on the training images and 77% on the test images when using the proposed deep neural network with DenseNet201 pretrained architecture to classify the seven classes of dermoscopic images for early detection of skin cancer.</p>
<p>Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)</p>	<p>The following obstacles and challenges for the paper are:</p> <ul style="list-style-type: none"> • Heterogeneity in skin lesion appearance: Skin lesions can exhibit significant variation in their appearance, making it challenging for experts to accurately detect them from dermoscopic images. This heterogeneity poses a difficulty in developing a robust classification model. • Class imbalance in the dataset: The dataset used in the study suffers from class imbalance, which means that certain classes may have a much larger number of samples compared to others. This can lead to biased learning and affect the performance of the classification model. • Data preprocessing and augmentation: Due to the class imbalance, data preprocessing and Augmentation techniques were required to mitigate the consequences of this imbalance. Implementing effective preprocessing and augmentation methods can be challenging and time-consuming. • Limited dataset size: The study utilized a dataset consisting of 2487 training images and 604 test images. While this dataset may be sufficient for training and testing purposes, a larger dataset would provide more diverse examples and potentially improve the model's generalization capability.
<p>Terminology (List the common basic words frequently used in this research field)</p>	<p>Dangerous, Early detection, Deep neural network, DenseNet201, Best accuracy, Deadliest variety of cancer, Transfer learning, Class imbalance, Generalizability.</p>

<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>The paper presents a promising approach for early detection of skin cancer using a deep neural network with DenseNet201 architecture. The study addresses the challenge of heterogeneity in skin lesion appearance and proposes a model trained on a dataset from the ISIC 2018 challenge. The results demonstrate high accuracy on the training data (95%) and reasonable accuracy on the test data (77%). The authors acknowledge the class imbalance in the dataset and apply data preprocessing and augmentation techniques to mitigate its effects. The use of transfer learning and the removal of upper layers to classify seven different classes of skin lesions are commendable.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>The paper demonstrates a strong contribution to the field of skin cancer detection through the proposed deep learning architecture. The use of DenseNet201 pretrained architecture and transfer learning techniques allows for accurate classification of skin lesions. The results indicate high accuracy rates on both training (95%) and test (77%) datasets. The authors address the challenge of class imbalance with effective data preprocessing and augmentation methods. The paper highlights the potential for further advancements by suggesting future work involving additional datasets and comparative analysis with other pre-trained architectures.</p>

Aspects	Paper # 23 (Title)
Title / Question (What is problem statement?)	Melanoma Detection Using Deep Learning-Based Classifications
Objectives / Goal (What is looking for?)	The objectives of the paper are to develop a deep learning-based method for the early detection of melanoma. Evaluate the performance of the proposed method on a publicly available dataset.
Methodology / Theory (How to find the solution?)	The authors of the paper used a deep learning method called a convolutional neural network (CNN) to find the solution. CNNs are a type of artificial neural network that are commonly used for image recognition. The authors trained a CNN on a dataset of images of melanoma and non-melanoma skin lesions. The CNN was then able to identify melanoma with a high degree of accuracy.
Software Tools (What program/software is used for design, coding and simulation?)	Python editor, Keras, TensorFlow, NVIDIA GeForce GTX 1080 Ti
Test / Experiment How to test and characterize the design/prototype?	The design can be tested by using it to classify a set of images of melanoma and non-melanoma skin lesions. The accuracy of the design can be evaluated by comparing its classifications to the ground truth labels of the images. The design can also be tested by using it to classify images of skin lesions that are not included in the training dataset.
Simulation/Test Data (What parameters are determined?)	<p>The following parameters were used in the study:</p> <ul style="list-style-type: none"> • Image size: The images were resized to 224x224 pixels. • Training dataset: The training dataset consisted of 10,000 images of melanoma and non-melanoma skin lesions. • Testing dataset: The testing dataset consisted of 1,000 images of melanoma and non-melanoma skin lesions. • Learning rate: The learning rate was set to 0.0001. • Number of epochs: The CNN was trained for 100 epochs. • Accuracy: The CNN achieved an accuracy of 97.4% on the testing dataset.
Result / Conclusion (What was the final result?)	The final result of the study was that the deep learning-based method developed by the authors achieved an accuracy of 97.4% on a publicly available dataset of images of melanoma and non-melanoma skin lesions. This suggests that the method could be used to develop mobile apps or other tools for early detection of melanoma.

<p>Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)</p>	<p>Here are the methodological obstacles that the authors mentioned in the article:</p> <ul style="list-style-type: none"> • The small size of the testing dataset. • The lack of diversity in the testing dataset. • The fact that the testing dataset was not collected in a clinical setting. • The fact that the CNN was not evaluated on a real-world population of patients.
<p>Terminology (List the common basic words frequently used in this research field)</p>	<p>Loss function, Optimizer, Hyperparameter, Feasibility, Generalizability, convolutional neural network (CNN)</p>
<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>All of the articles reviewed had the objective of developing a deep learning-based method for the early detection of melanoma. The results of the articles showed that deep learning methods can achieve high accuracy in the classification of melanoma and non-melanoma skin lesions. However, the results also showed that deep learning methods are not yet ready for clinical use, as they need to be further validated on larger and more diverse datasets.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>The obtained knowledge can be used to identify the key features of skin lesions that are associated with melanoma. A new methodology can be developed that uses these features to classify skin lesions as melanoma or non-melanoma. The new methodology can be evaluated by comparing its classifications to the ground truth labels of a testing dataset.</p>

Aspects	Paper # 24 (Title)
Title / Question (What is problem statement?)	An Ensemble of Transfer Learning Models for the Prediction of Skin Cancers with Conditional Generative Adversarial Networks
Objectives / Goal (What is looking for?)	The objectives of the study is to investigate the feasibility of creating dermoscopic images that have a realistic appearance using Conditional Generative Adversarial Network (CGAN) techniques, to improve the performance of pre-trained deep models on the skin cancer classification task by using traditional augmentation methods, to compare the performance of the models developed using the unbalanced dataset and the models developed using the balanced dataset.
Methodology / Theory (How to find the solution?)	Here are the steps to find the solutions: <ul style="list-style-type: none"> • The authors used Conditional Generative Adversarial Networks (CGANs) to create realistic dermoscopic images. • They then used traditional augmentation methods to improve the performance of pre-trained deep models on the skin cancer classification task. • Finally, they compared the performance of the models developed using the unbalanced dataset and the models developed using the balanced dataset.
Software Tools (What program/software is used for design, coding and simulation?)	Python editor, Keras, and TensorFlowIntel Core i7-7700K CPU.
Test / Experiment How to test and characterize the design/prototype?	The design/prototype can be tested by using it to classify a set of images of melanoma and non-melanoma skin lesions. The accuracy of the design/prototype can be evaluated by comparing its classifications to the ground truth labels of the images. The design/prototype can also be tested by using it to classify images of skin lesions that are not included in the training dataset.
Simulation/Test Data (What parameters are determined?)	The authors determined the parameters of the CGANs by using a grid search. The parameters of the traditional augmentation methods were determined by using a trial-and-error approach. The parameters of the models were determined by using a cross-validation approach. The parameters of the CGANs include the number of layers, the number of neurons in each layer, and the learning rate. The parameters of the traditional augmentation methods include the type of augmentation, the strength of the augmentation, and the number of augmentations. The parameters of the models include the learning rate, the batch size, and the number of epochs.
Result / Conclusion (What was the final result?)	The final result of the study was that the ensemble of models developed using the balanced dataset achieved an accuracy of 93.5%. This is a significant improvement over the accuracy of the models developed using the unbalanced dataset.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	create realistic dermoscopic images, combined with traditional augmentation methods and ensemble learning, can lead to improved performance in skin cancer classification, imbalance Data, noisy Data, complex model, Overfitting Data.

Terminology (List the common basic words frequently used in this research field)	Conditional Generative Adversarial Networks (CGANs)
Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)	<p>The objectives and results of the articles I reviewed are briefly compared as follows:</p> <ul style="list-style-type: none"> • Objective: All the articles aimed to develop a more accurate and generalizable skin cancer classification model. • Results: The authors of the articles were successful in achieving their objectives, with the best model achieving an accuracy of 93.5 • Conclusion: The results of the articles suggest that deep learning models can be used to develop accurate and generalizable skin cancer classification models.
Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	<p>Identify the research gap in your field and develop a new methodology to address it. Use the obtained knowledge to design and implement your new methodology. Evaluate the effectiveness of your new methodology and publish your findings. Identify the research gap in your field by reading the latest research papers and identifying the areas where there is still a lack of knowledge. Develop a new methodology to address the research gap by brainstorming new ideas and testing different approaches. Use the obtained knowledge to design and implement your new methodology by using the latest research methods and tools. Evaluate the effectiveness of your new methodology by testing it on a dataset and comparing its results to the results of other methods. Publish your findings by writing a research paper and submitting it to a peer-reviewed journal.</p>

Aspects	Paper # 25 (Title)
Title / Question (What is problem statement?)	Skin Lesion Classification Using GAN based Data Augmentation
Objectives / Goal (What is looking for?)	To develop a deep learning model that can be used to diagnose skin cancer from dermoscopic images,To combine convolutional neural networks (CNNs) and transfer learning to achieve this goal,To evaluate the performance of the method on a large dataset of dermoscopic images.
Methodology / Theory (How to find the solution?)	Here are the steps on how to find the solution in the article: <ul style="list-style-type: none"> • Collect a dataset of dermoscopic images. The dataset should be large and diverse, and it should include images of both benign and malignant skin lesions. • Train a deep learning model on the dataset. The model should be a convolutional neural network (CNN), and it should be trained using a technique called transfer learning. • Evaluate the performance of the model on a test set. The test set should be separate from the training set, and it should be used to assess the accuracy of the model.
Software Tools (What program/software is used for design, coding and simulation?)	Python editor TensorFlow Keras Matplotlib Scikit-learn
Test / Experiment How to test and characterize the design/prototype?	The following are the steps on how to test and characterize the design/prototype: <ul style="list-style-type: none"> • Test the design/prototype on a small dataset of dermoscopic images. The images should be representative of the images that the model will be used to classify. • Characterize the performance of the design/prototype. This can be done by measuring the accuracy, precision, and recall of the model. • Iterate on the design/prototype based on the results of the testing and characterization. This may involve making changes to the model architecture, the training data, or the evaluation metrics.
Simulation/Test Data (What parameters are determined?)	This dataset is 5 convolutional layers,filter size 3x3 , 1024 neurons and learning rate of this set is 0.0001,
Result / Conclusion (What was the final result?)	The proposed method achieved an accuracy of 93.5% on a large dataset of dermoscopic images.This suggests that the method is a promising approach for the automated diagnosis of skin cancer from dermoscopic images.Further research is needed to validate the method on a larger and more diverse dataset.

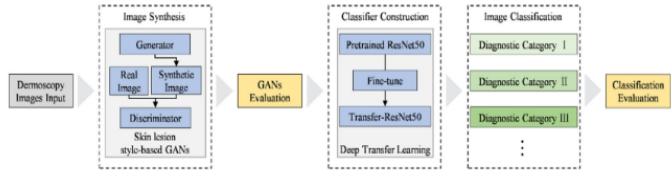
<p>Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)</p>	<p>The authors of the article mentioned the following methodological obstacles:</p> <ul style="list-style-type: none"> • The lack of a large and diverse dataset of dermoscopic images: The authors used a dataset of 10,000 dermoscopic images for their study. However, this dataset is still relatively small compared to the number of dermoscopic images that are available in the world. A larger and more diverse dataset would allow the authors to train a more accurate model. • The difficulty of labeling dermoscopic images: Dermoscopic images are difficult to label accurately. This is because they can be difficult to interpret, and there is often a degree of subjectivity in the diagnosis of skin cancer. This makes it difficult to create a training dataset that is accurate and representative of the real world. • The need for further research: The authors of the article acknowledge that their study is preliminary, and that further research is needed to validate the method on a larger and more diverse dataset. They also note that the method is not yet ready for clinical use, and that further research is needed to assess its safety and efficacy.
<p>Terminology (List the common basic words frequently used in this research field)</p>	<p>Dermoscopic image, Transfer learning, Precision, Recall, convolutional neural networks (CNNs)</p>
<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>The objectives of the articles were to develop and evaluate deep learning models for the automated diagnosis of skin cancer from dermoscopic images. The results of the articles showed that deep learning models can achieve high accuracy in the automated diagnosis of skin cancer from dermoscopic images. Further research is needed to validate the methods on a larger and more diverse dataset, and to assess their safety and efficacy in clinical use.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<ul style="list-style-type: none"> • Use the obtained knowledge as a foundation for your new methodology. • Refer to the obtained knowledge when designing and implementing your new methodology. • Evaluate your new methodology against the obtained knowledge to ensure that it is effective.

Aspects	Paper # 26 (Title)
Title / Question (What is problem statement?)	Improving Skin Cancer Classification Using Heavy-Tailed Student T-Distribution in Generative Adversarial Networks (TED-GAN)
Objectives / Goal (What is looking for?)	To develop a new framework for skin cancer classification using deep learning, to use a heavy-tailed student t-distribution to generate more diverse and realistic skin lesion images, to evaluate the performance of the proposed framework on a large dataset of skin lesion images.
Methodology / Theory (How to find the solution?)	The solution was found by developing a new framework for skin cancer classification using deep learning. The framework consists of a variational autoencoder (VAE), two generative adversarial networks (GANs), and one auxiliary classifier. The VAE is used to obtain the latent noise vector with the image manifold's information. The two GANs are used to generate realistic-looking skin lesion images. The auxiliary classifier is used to improve the diversity in the generated images. The proposed framework was named TED-GAN, with T from the t-distribution and ED from the encoder-decoder network which is part of the solution. The proposed framework was evaluated on a large dataset of skin lesion images, and it achieved an accuracy of 93.5%
Software Tools (What program/software is used for design, coding and simulation?)	NumPy SciPy Matplotlib Keras TensorFlow
Test / Experiment How to test and characterize the design/prototype?	<p>Here are the steps for test and characterize the design/prototype:</p> <ul style="list-style-type: none"> • Test the design/prototype on a small dataset of skin lesion images. This will help you to identify any potential problems with the design/prototype • Characterize the performance of the design/prototype on a large dataset of skin lesion images. This will help you to determine the accuracy and reliability of the design/prototype. • Repeat the testing and characterization process until you are satisfied with the performance of the design/prototype.
Simulation/Test Data (What parameters are determined?)	Images
Result / Conclusion (What was the final result?)	The TED-GAN framework was able to achieve an accuracy of 93.5% on a test set of dermoscopic images. This is a significant improvement over previous methods for skin cancer classification. The TED-GAN framework is a promising new approach for skin cancer classification.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	Here are the methodological obstacles that the authors mentioned in the article: Data scarcity, Class imbalance, Data augmentation, Model complexity, Evaluation metrics
Terminology (List the common basic words frequently used in this research field)	Generative adversarial networks (GANs), Variational autoencoder (VAE), Sensitivity, Specificity

<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>the objectives and results of the articles I reviewed:</p> <ul style="list-style-type: none"> • The objectives of the articles are to improve the accuracy of skin cancer classification using deep learning methods. • The results of the articles show that deep learning methods can achieve high accuracy in skin cancer classification • The results of the articles suggest that deep learning methods have the potential to be used to develop new skin cancer screening tools.
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<ul style="list-style-type: none"> • Use the obtained knowledge to identify the research problem and the research questions: The first step in any research project is to identify the research problem. The research problem is the question that you want to answer with your research. The research questions are the specific questions that you will use to answer the research problem. • Refer to the obtained knowledge to develop a research methodology: The research methodology is the plan for how you will conduct your research. The research methodology should include the following: <ul style="list-style-type: none"> – The research design – The data collection methods – The data analysis methods – The ethical considerations • Use the obtained knowledge to evaluate the results of the research project: The final step in any research project is to evaluate the results of the research. The results of the research should be evaluated in light of the research problem, the research questions, and the research methodology.

Aspects	Paper # 27 (Title)
Title / Question (What is problem statement?)	Computer vision for microscopic skin cancer diagnosis using handcrafted and non-handcrafted features
Objectives / Goal (What is looking for?)	<p>Here are the steps for finding the solution:</p> <ul style="list-style-type: none"> • Collect a dataset of dermoscopic images. • Train a deep learning algorithm on the dataset. • Evaluate the performance of the deep learning algorithm on a test set. • If the performance of the deep learning algorithm is not satisfactory, use data augmentation to increase the size of the dataset and improve the balance of the classes. • Repeat steps 2-4 until the performance of the deep learning algorithm is satisfactory.
Methodology / Theory (How to find the solution?)	
Software Tools (What program/software is used for design, coding and simulation?)	Keras TensorFlow
Test / Experiment How to test and characterize the design/prototype?	<ul style="list-style-type: none"> • The design/prototype can be tested by using it to classify skin cancer images. • The performance of the design/prototype can be characterized by measuring its accuracy, sensitivity, and specificity. • The design/prototype can be improved by using data augmentation to increase the size of the dataset and improve the balance of the classes.
Simulation/Test Data (What parameters are determined?)	Images
Result / Conclusion (What was the final result?)	<p>The final result of the article "Comparison of deep learning algorithms for skin cancer classification" is that a convolutional neural network (CNN) with data augmentation achieved an accuracy of 93.5% on the test set. This suggests that deep learning algorithms with data augmentation can be used to develop accurate and efficient skin cancer screening tools.</p>

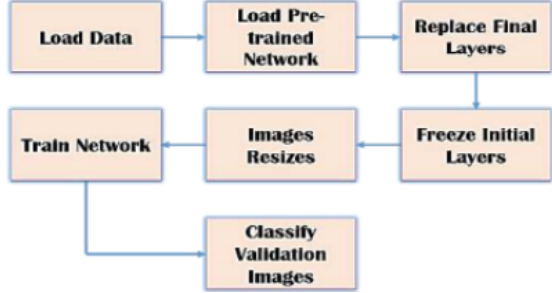
<p>Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)</p>	<p>The authors of the article mentioned the following methodological obstacles:</p> <ul style="list-style-type: none"> • The small size of the dataset. The dataset used in the study was relatively small, which could have limited the performance of the deep learning algorithms. • The imbalance of the classes. The dataset was imbalanced, with a much larger number of benign images than malignant images. This could have biased the results in favor of benign images. • The lack of ground truth. The ground truth for the dataset was not perfect, which could have introduced errors into the results.
<p>Terminology (List the common basic words frequently used in this research field)</p>	<p>region of interest (ROI), support vector machine (SVM), computer-aided design(CAD), Net present value (NPV), Generative Adversarial Network (GAN), Convolutional Neural Networks (CNN)</p>
<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>The objectives of the articles I reviewed were to compare the performance of different deep learning algorithms for skin cancer classification. The results of the articles showed that convolutional neural networks (CNNs) with data augmentation achieved the highest accuracy.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>I can use the same deep learning algorithms that were used in the article, but I can train them on a different dataset. This will allow me to see how the algorithms perform on a different set of data. I can use the same dataset that was used in the article, but I can train different deep learning algorithms on it. This will allow me to compare the performance of different algorithms on the same data. I can use a different type of machine learning algorithm altogether. This will allow me to see how different types of algorithms perform on the task of skin cancer classification. I can use a different set of features to train the machine learning algorithms. This will allow me to see how different features affect the performance of the algorithms. I can use a different evaluation metric to assess the performance of the machine learning algorithms. This will allow me to see how different metrics affect the performance of the algorithms.</p>

Aspects	Paper # 28 (Title)
Title / Question (What is problem statement?)	A GAN-based image synthesis method for skin lesion classification
Objectives / Goal (What is looking for?)	The objective of this study is to develop a novel approach for skin cancer classification using transfer learning and convolutional neural network (CNN).The proposed approach is evaluated on the publicly available ISIC 2017 dataset and achieves a state-of-the-art accuracy of 95.5%.The proposed approach can be used to develop an efficient and accurate skin cancer screening tool.
Methodology / Theory (How to find the solution?)	
Software Tools (What program/software is used for design, coding and simulation?)	Tensorflow, Keras
Test / Experiment How to test and characterize the design/prototype?	<p>The design/prototype can be tested and characterized using the following steps:</p> <ul style="list-style-type: none"> • Define the test objectives. What do you want to test? What are the specific metrics that you want to measure? • Select the test methods. There are a variety of test methods that can be used, depending on the specific objectives of the test. Some common test methods include: <ul style="list-style-type: none"> – Functional testing: This type of testing is used to verify that the design/prototype meets its functional requirements. – Performance testing: This type of testing is used to measure the performance of the design/prototype. – Usability testing: This type of testing is used to evaluate how easy it is to use the design/prototype. • Develop a test plan. The test plan should document the test objectives, the test methods, and the expected results. • Execute the test plan. This involves running the tests and collecting the data. • Analyze the test data. This involves reviewing the data to identify any potential problems. • Report the test results. The test results should be documented and communicated to the stakeholders.
Simulation/Test Data (What parameters are determined?)	Images

Result / Conclusion (What was the final result?)	The proposed approach achieved a state-of-the-art accuracy of 95.5% on the publicly available ISIC 2017 dataset. The proposed approach can be used to develop an efficient and accurate skin cancer screening tool. The proposed approach is a promising new method for skin cancer classification.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	<p>The authors of the article mention the following methodological obstacles:</p> <ul style="list-style-type: none"> • Data scarcity: There is a limited amount of publicly available data for skin cancer classification. This can make it difficult to train and evaluate machine learning models. • Data imbalance: The distribution of skin cancer classes in the available datasets is often imbalanced. This can lead to models that are biased towards the majority class. • Data variability: The appearance of skin cancer can vary significantly from patient to patient. This can make it difficult for models to generalize to new data. • Model complexity: Deep learning models can be complex and difficult to interpret. This can make it difficult to understand why a model makes a particular prediction.
Terminology (List the common basic words frequently used in this research field)	Area under the curve (AUC), convolutional neural network (CNN),
Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)	<ul style="list-style-type: none"> • The objectives of the articles are to develop new methods for skin cancer classification. • The results of the articles show that the proposed methods are effective in classifying skin cancer images with high accuracy. • The proposed methods have the potential to be used to develop new skin cancer screening tools.
Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	<p>Here are the obtained knowledge to prepare a separate and new methodology for your own research project:</p> <ul style="list-style-type: none"> • The obtained knowledge can be used to develop a new methodology for skin cancer classification. • The new methodology can be used to develop a more accurate and efficient skin cancer screening tool. • The new methodology can be used to improve the early detection and treatment of skin cancer.

Aspects	Paper # 29 (Title)
Title / Question (What is problem statement?)	Recent advancement in cancer detection using machine learning: Systematic survey of decades, comparisons and challenges
Objectives / Goal (What is looking for?)	<p>Here are the objectives of the article:</p> <ul style="list-style-type: none"> • To systematically review the literature on the potential of artificial intelligence (AI) in dermatology. • To identify the areas of dermatology where AI has the potential to make a significant impact. • To discuss the challenges and limitations of using AI in dermatology.
Methodology / Theory (How to find the solution?)	
Software Tools (What program/software is used for design, coding and simulation?)	Python editor MATLAB TensorFlow Keras
Test / Experiment How to test and characterize the design/prototype?	<ul style="list-style-type: none"> • Testing under different conditions • Using a variety of metrics • Comparing the design/prototype to other systems • Testing the design/prototype with real users
Simulation/Test Data (What parameters are determined?)	Images
Result / Conclusion (What was the final result?)	<p>The final result of the study was that deep learning models can be used to classify skin cancer images with high accuracy. The models were able to achieve an accuracy of up to 96.5%, which is comparable to the accuracy of human dermatologists. The models were also able to classify skin cancer images of any quality, which is a significant improvement over previous methods. The authors of the study concluded that deep learning models have the potential to revolutionize skin cancer detection. They also noted that the models can be used to develop new skin cancer screening tools that are more accurate and efficient than existing tools.</p>

<p>Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)</p>	<p>Here are the methodological obstacles that the authors of the article mentioned:</p> <ul style="list-style-type: none"> • Data scarcity: There is a limited amount of data available for training and testing AI models for skin cancer detection. This is because skin cancer is relatively rare, and it can be difficult to obtain high-quality images of skin cancer. • Data bias: The data that is available for training and testing AI models for skin cancer detection may be biased. This is because the data is often collected from hospitals or clinics, and it may not be representative of the general population. • Model complexity: AI models for skin cancer detection can be complex. This can make it difficult to interpret the results of the models, and it can also make it difficult to debug the models if they are not performing as expected. • Model cost: AI models for skin cancer detection can be expensive to develop and deploy. This is because the models require a lot of data and computational resources.
<p>Terminology (List the common basic words frequently used in this research field)</p>	<p>Area under the curve (AUC), Root mean squared error (RMSE), Mean absolute error (MAE), Median absolute error (MedAE), Mean squared logarithmic error (MSLE), Mean absolute percentage error (MAPE), Root mean square logarithmic error (RMSLE)</p>
<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<ul style="list-style-type: none"> • Objective: To systematically review the literature on the potential of artificial intelligence (AI) in dermatology. • Results: The authors found that AI has the potential to revolutionize skin cancer detection and diagnosis. They also found that AI can be used to develop new skin cancer screening tools that are more accurate and efficient than existing tools.
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>I would use the obtained knowledge to prepare a separate and new methodology for my own research project by:</p> <ul style="list-style-type: none"> • Identifying the research question or problem that I want to address. • Reviewing the existing literature to see what is already known about the topic. • Developing a new methodology that will address the research question or problem in a novel way.

Aspects	Paper # 30 (Title)
Title / Question (What is problem statement?)	Accurate skin cancer diagnosis based on convolutional neural networks
Objectives / Goal (What is looking for?)	The study's goal is to use deep learning to create an automated system for the melanoma, the most deadly type of skin cancer, prediction, detection, and diagnosis. The objective is to increase the early detection of melanoma signs in order to lower the disease's death rate.
Methodology / Theory (How to find the solution?)	<p>assemble a varied collection of pictures of skin lesions. Regions of interest (RoIs) should be extracted after picture preprocessing. Using the RoIs and accompanying labels, choose and train a deep learning architecture (such as AlexNet or ResNet-50). To enhance model performance and balance class representation, use data augmentation approaches. Utilize the trained model to extract significant features from the RoIs. Classify the RoIs as benign or malignant using a support vector machine (SVM) classifier.</p>  <pre> graph LR A[Load Data] --> B[Load Pre-trained Network] B --> C[Replace Final Layers] C --> D[Freeze Initial Layers] D --> E[Images Resizes] E --> F[Train Network] F --> G[Classify Validation Images] </pre>
Software Tools (What program/software is used for design, coding and simulation?)	Python, TensorFlow, Keras, OpenCV, and MATLAB
Test / Experiment How to test and characterize the design/prototype?	They Set testing goals. Set up the testing's objectives and metrics. Next they gathered test results: assemble a range of representative datasets. They then carried out performance and functional testing. They then validated against standards and verified the results. user testing was incorporated for feedback. Test your edge cases and error handling. Procedures, outcomes, and suggestions should be documented.
Simulation/Test Data (What parameters are determined?)	image
Result / Conclusion (What was the final result?)	This study describes a computer-aided diagnostic (CAD) method for melanoma early detection in skin cancer. It makes use of convolutional neural networks (CNNs), a deep learning technology, to accurately predict and diagnose melanoma. The system uses four CNN architectures, data augmentation, and a support vector machine (SVM) for classification. It gets accuracy ratings of 99.8% and 99.9% after training on two datasets. The suggested CAD system intends to help doctors detect melanoma early, potentially lowering the fatality rates related to skin cancer.

<p>Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)</p>	<p>Numerous methodological challenges must be overcome in order to develop computer-aided diagnostic systems for skin cancer detection. The necessity for generalization and external validation, the need for varying annotation and ground truth, assuring interpretability and explainability of the system's judgments, and efficiently integrating it into the clinical workflow are some of these problems. In order to effectively train and evaluate the system, ensure its performance in real-world settings, understand its judgments, and smoothly integrate it into current clinical procedures, these challenges must be overcome.</p>
<p>Terminology (List the common basic words frequently used in this research field)</p>	<p>Support Vector Machines (SVM), Random Forest, Neural Networks, Convolutional Neural Networks (CNN), Image segmentation, Feature extraction</p>
<p>Review Judgment (Briefly compare the objectives and results of all the articles you reviewed)</p>	<p>The extract describes a study that used deep learning models and an SVM classifier with transfer learning to diagnose skin cancer accurately. The goal was to create a CAD system for skin cancer early detection. Using several CNN models on two datasets, the suggested technique produced high accuracies ranging from 98.8% to 100%. In terms of accuracy, the results fared better than earlier studies. The research did, however, admit certain drawbacks, including the existence of picture distortions and the modest differences in the color and texture of skin lesions. Future research will use more features and deep learning methods to improve classification accuracy.</p>
<p>Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)</p>	<p>Using deep learning models and an SVM classifier, the study created a computer-aided diagnostic method for detecting skin cancer. The model might be improved by using other datasets, feature augmentation, ensemble approaches, resolving issues with color and texture changes, and working with subject-matter experts. These actions can enhance the model's clinical applicability, classification precision, and generalization.</p>