# Skin Cancer Classification and Segmentation Using Lenet

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***Abstract- Skin cancer is one of the most prevalent types of cancer worldwide, and early detection plays a crucial role in improving patient outcomes. The classification aspect focuses on distinguishing between benign and malignant skin lesions. Various AI algorithms, including machine learning and deep learning models, are explored for this task. The segmentation aspect addresses the precise delineation of skin lesions from surrounding healthy tissue. AI techniques such as convolutional neural networks (CNNs) and image processing algorithms are utilized for accurate lesion segmentation.***

***Index Terms- Skin Cancer, Lenet Architecture, Deep Learning, Convolutional Neural Networks, Segmentation, Image Processing.***

## I. INTRODUCTION

Skin cancer poses a significant global health threat, marked by increasing incidence rates and potentially dire consequences if not detected and treated promptly. Leveraging advanced technologies, such as Artificial Intelligence (AI), has become a promising avenue to enhance the accuracy and efficiency of skin cancer diagnosis. Among various AI techniques, Convolutional Neural Networks (CNNs) have gained prominence for their effectiveness in image classification and segmentation tasks. Developed by Yann LeCun in the 1990s, LeNet architecture represents one of the pioneering CNN designs that laid the foundation for modern deep learning approaches. In recent years, the fusion of medical science with AI has sparked excitement within the dermatological community. This integration holds immense potential for revolutionizing dermatology by enabling the development of robust systems capable of accurately classifying different types of skin lesions and segmenting affected regions within images. By harnessing machine learning algorithms and deep learning models, researchers and clinicians aim to create automated, objective, and rapid diagnostic tools. Ultimately, this convergence of AI techniques seeks to improve patient outcomes by providing timely and precise diagnoses, thereby addressing the challenges posed by skin cancer more effectively.

## II. LITERATURE SURVEY

| TITLE, YEAR PUBLISHED, AUTHORS | ALGORITHM | PROS | CONS |
|---|---|---|---|
| Multiview Robust Graph-Based Clustering for Cancer Subtype Identification, January/ February 2023, Xiaofeng Shi, Cheng Liang , and Hong Wang. | Multiview Robust Graph-Based Clustering | • Handles multi omics<br>• Robust to noise in data<br>• Adaptive learning of similar matrices | • Sensitive in nature<br>• Expensive not cost efficient |
| Artificial Intelligence-Based Image Classification for Diagnosis of Skin Cancer: Challenges and Opportunities, December 2020, Manu Goyal, Thomas Knackstedt, Shaofeng Yan and Saeed Hassanpour. | Image Classification for Diagnosis of Skin Cancer | • High Accuracy<br>• Rapid Diagnosis<br>• Scalability | • Overfitting<br>• Dependency on Image Quality<br>• Regulatory Challenges |
| Detection and Classification of Skin Cancer by Using a Parallel CNN Model, December 2020, Noortaz Rezaoana, Mohammad Shahadat Hossain, Karl Andersson. | Parallel CNN Mode | • Efficient Parallel Processing<br>• Improved Classification Accuracy<br>• Scalability | • Increased Complexity<br>• Resource Intensive |

Table 1-Literature survey

## III. EXISTING SYSTEM

Cancer subtype identification is a crucial aspect of cancer research, involving the classification of cancer into distinct groups based on their molecular characteristics and clinical manifestations. This process lays the groundwork for more personalized diagnosis and therapy, as it enables healthcare professionals to tailor treatment strategies to specific subtypes of cancer. With the advent of public datasets such as The Cancer Genome Atlas (TCGA), which have amassed vast amounts of multi-omics data, researchers now have unprecedented opportunities to delve into the intricacies of cancer biology and unveil its underlying mechanisms at a comprehensive level.
In this context, our paper introduces a novel approach called multi-view robust graph-based clustering (MRGC) to effectively identify cancer subtypes. Our method begins by learning robust latent representations from the raw omics data, aiming to mitigate the influence of noise inherent in biological datasets. Subsequently, a series of similarity matrices are adaptively learned based on these refined representations, capturing the intricate relationships between different molecular features. Finally, we construct a global similarity graph by leveraging the consensus structure obtained from these individual graphs.

The strength of our approach lies in the synergy between its three core components, each reinforcing the other in a mutual iterative manner. By integrating robust latent representation learning, adaptive similarity matrix construction, and global consensus graph formation, our method provides a comprehensive framework for identifying cancer subtypes with enhanced accuracy and robustness. Through empirical evaluation on real-world datasets, we demonstrate the effectiveness of MRGC in uncovering clinically relevant cancer subtypes, thereby contributing to the advancement of precision oncology and personalized cancer care.

## IV. ISSUES IN EXISTING SYSTEM

In the existing system, the utilization of machine learning methods for clustering cancer subtypes may not be the most effective approach. Rather than constructing predictive models, their method primarily focuses on analysis, potentially limiting its ability to generalize to new datasets or predict outcomes accurately. Moreover, the reliance on a single architecture may overlook the nuances and complexities present in cancer data, hindering the system's capacity to capture diverse molecular profiles effectively. Additionally, the scope of their analysis appears limited, as they only investigate four subtypes of cancer, potentially neglecting other clinically significant variations. Critically, the system's performance metrics, such as accuracy, remain undisclosed, raising questions about its reliability and validity. To address these limitations, future efforts could explore the integration of multiple architectures, leverage larger and more diverse datasets, and prioritize the development of predictive models to enhance the accuracy and robustness of cancer subtype identification systems.

## V. PROPOSED SYSTEM

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## VI. METHODOLOGIES

*a.CNN:*

Convolutional Neural Networks (CNNs) have emerged as a cornerstone in the realm of deep learning, particularly renowned for their prowess in handling image data. Introduced as a groundbreaking architecture, CNNs revolutionized computer vision tasks by automatically learning hierarchical features from raw pixel inputs, alleviating the need for handcrafted feature engineering.

Their unique design, characterized by convolutional layers followed by pooling operations, enables CNNs to effectively capture spatial hierarchies and patterns within images, making them exceptionally well-suited for tasks such as image classification, object detection, and segmentation.

*b. Participation of Data Science:*

Data science is an interdisciplinary field that uses scientific methods, processes, algorithms and systems to extract knowledge and insights from structured and unstructured data, and apply knowledge and actionable insights from data across a broad range of application domains. Data science can be defined as a blend of mathematics, business acumen, tools, algorithms and machine learning techniques, all of which help us in finding out the hidden insights or patterns from raw data which can be of major use in the formation of big business decisions.

*c. Data Visualization:*

Data visualization involves presenting model performance metrics like accuracy, precision, recall, and F1-score through plots and graphs. Segmentation results are displayed via heatmaps or overlays, aiding in understanding the model's decisions and enabling medical professionals to interpret and validate predictions, thereby enhancing skin cancer diagnosis and treatment.

*d. Artificial intelligence:*

Artificial intelligence in skin cancer classification and segmentation is a significant advancement in dermatological diagnosis. By leveraging deep learning algorithms, CNNs can effectively analyze large datasets of dermatological images, accurately distinguishing between benign and malignant skin lesions. This technology not only enhances the efficiency of diagnosis but also facilitates early detection and treatment planning, potentially saving lives.

*e. Inclusion of Deep Learning:*

The classification and segmentation of skin cancer lesions using Convolutional Neural Networks (CNNs) is a prominent application of deep learning in medical imaging. CNNs can effectively analyze dermatological images to distinguish between benign and malignant lesions, aiding in early diagnosis and treatment. By leveraging CNN technology, researchers have developed robust models capable of accurately identifying and delineating various types of skin cancer, contributing to improved patient outcomes and healthcare efficiency.

In disease approximately 100 billion neurons all together this is a picture of an individual neuron and each neuron is connected through thousands of their neighbors. The question here is how it recreates these neurons in a computer. So, it creates an artificial structure called an artificial neural net where we have nodes or neurons. It has some neurons for input value and some for output value and in between, there may be lots of neurons interconnected in the hidden layer. Artificial neural networks (ANNs) were inspired by information processing and distributed communication nodes in biological systems. ANNs have various differences from biological disease. Specifically, neural networks tend to be static and symbolic, while the biological disease of most living organisms is dynamic (plastic) and analogue.

*f. Machine Learning:*

Machine learning is a subset of artificial intelligence (AI) that focuses on the development of algorithms and statistical models that enable computers to perform a specific task without being explicitly programmed for that task.

## VII. DATASET

This dataset contains approximately 3000 images for training and 180 images for testing ,which are then classified into 9 classes of skin cancer.

*a.Feasibility Study:*

*Splitting the dataset:*

The data use is usually split into training data and test data. The training set contains a known output and the model learns on this data in order to be generalized to other data later on. It has the test dataset (or subset) in order to test our models and it will do this using the Tensor flow library in Python using the Keras method.

*Construction of a Detecting Model:*

Deep learning needs data gathering and has a lot of past image data. Training and testing this model working and predicting correctly.

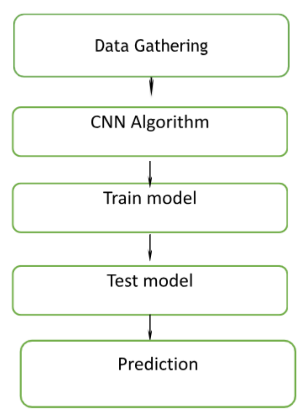



Figure 1: Detecting Model

The nine types of skin cancer detected are:

1. Fibroma
2. Melanoma
3. Nevus
4. Pigmented benign keratosis

5. Seborrhea keratosis
6. Squamous cell carcinoma
7. Vascular lesion

## VIII. SYSTEM DESCRIPTION

*a.Project goal:*

The goal of the project is to develop a robust and efficient system for the classification and segmentation of skin cancer using artificial intelligence (AI) techniques. Skin cancer is a prevalent and potentially life-threatening disease, with early detection playing a crucial role in successful treatment. Traditional methods of diagnosis rely heavily on the expertise of dermatologists, which can lead to delays in diagnosis and treatment. By harnessing the power of AI, specifically deep learning and image analysis techniques, this project aims to create a system that can accurately classify different types of skin lesions and provide precise segmentation to aid in diagnosis.

*b.Objective:*

The primary objective is to train a deep learning model using a large dataset of diverse skin lesion images to achieve high accuracy in classifying skin cancer types, including melanoma, basal cell carcinoma, and squamous cell carcinoma. Additionally, the project aims to develop a segmentation model that can precisely outline the boundaries of skin lesions, aiding in the identification and analysis of the affected areas. The goal is to create a comprehensive solution that combines accurate classification with detailed segmentation, enabling healthcare professionals to make informed decisions about patient care.

The project scope encompasses the development of a comprehensive system for the classification and segmentation of skin cancer utilizing advanced Artificial Intelligence (AI) techniques. Skin cancer is a prevalent and potentially life-threatening disease that requires early detection for effective treatment. The proposed system aims to leverage cutting-edge AI algorithms to enhance the accuracy and efficiency of skin cancer diagnosis. By integrating machine learning and image processing techniques, the system will analyze dermatological images to classify and segment different types of skin lesions, contributing to the early identification of skin cancer.

*c.System Architecture:*

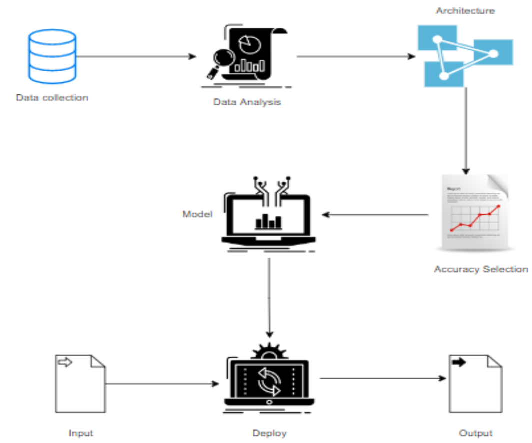



Figure 2:System Architecture

1. Data Collection: Gather skin cancer images from online repositories along with corresponding labels
2. Data Analysis: Analyze data characteristics, quality, and distribution, addressing biases and inconsistencies. Preprocess data through normalization, resizing, or augmentation.
3. Architecture: Design AI system architecture, selecting deep learning models, feature extraction techniques, and training strategies. Determine neural network architecture, optimization algorithms, and loss functions.
4. Accuracy Selection: Define performance metrics such as accuracy, precision, recall, and F1-score. Establish criteria for acceptable performance.
5. Model Training: Train selected deep learning model on annotated skin cancer images. Optimize model parameters through backpropagation and minimize chosen loss function.
6. Deployment: Deploy trained model into production environment. Integrate model into software system for real-world use. Ensure scalability, performance monitoring, and model maintenance.

*d.Convolution Layer:*

Convolutional layers, fundamental in CNNs, extract features by sliding learnable kernels across input images, performing element-wise multiplication with local regions, and summing results to generate feature maps. Acting as feature detectors, these filters identify low-level features like edges and textures in skin lesion images. Stacked convolutional layers enable the network to learn complex features, with information deepening through the network. Parameters like kernel size and stride affect feature extraction, while the output serves as a foundation for subsequent layers to make higher-level decisions such as classification or segmentation.

*e.MaxPooling Layer and flattening process:*

The max-pooling layer plays a pivotal role alongside convolutional layers for feature extraction and dimensionality reduction. Typically configured with a 2x2 pool size, a stride of 2, and required padding, the max-pooling layer downsamples feature maps obtained from convolutional layers. By partitioning the feature map into non-overlapping 2x2 regions and retaining only the maximum value within each region, the layer effectively reduces spatial dimensions by a factor of two in both width and height. This downsampling aids in capturing the most salient features while discarding redundant information, thereby enhancing the network's ability to generalize and reducing computational complexity. Following max-pooling, the feature maps are typically flattened into a one-dimensional vector, enabling subsequent fully connected layers to perform higher-level tasks such as skin cancer classification or segmentation. This flattening process rearranges the spatial information into a linear format, facilitating the extraction of global features across the entire image. Together, convolutional layers, max-pooling layers with appropriate configurations, and flattening operations form a powerful framework for skin cancer classification and segmentation within CNN architectures.

*f.Segmentation using ANN:*

In a three-layer artificial neural network (ANN) comprising an input layer, a hidden layer, and an output layer, each layer serves a distinct purpose in the information processing pipeline.

The input layer consists of neurons corresponding to the features of the input data, often represented as small images. Each neuron represents a feature, and the values represent the intensity or presence of that feature in the input data. During processing, these neurons transmit their values to neurons in the hidden layer.

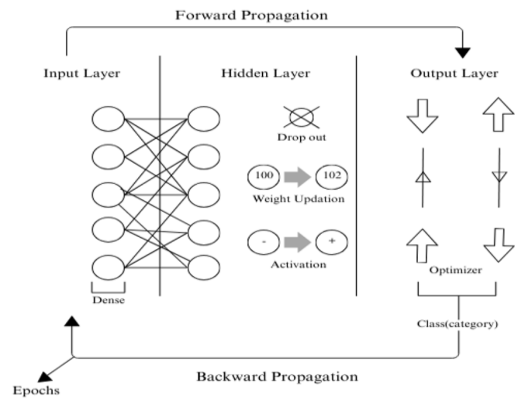



Figure 3: Segmentation process

The hidden layer processes the input data received from the input layer by applying weights to the connections between neurons. Neurons in the hidden layer sum the weighted inputs and pass the result through an activation function, which introduces non-linearity into the model. This layer serves to extract relevant features from the input data and transform them into a format that is more suitable for classification or regression tasks. Dropout may be applied in this layer to randomly remove some neurons during training, preventing overfitting by encouraging redundancy in the network's representation.

The output layer receives the processed data from the hidden layer and produces the final output of the network. Neurons in the output layer represent the classes or categories that the model predicts. Each neuron's output is computed based on the weighted sum of inputs from the hidden layer, followed by an activation function that converts the raw output into a probability distribution over the classes.

During training, forward propagation occurs, where input data is fed forward through the network, layer by layer, to produce predictions. Backward propagation, or backpropagation, is used to compute the gradient of the loss function with respect to the network's parameters. The optimizer adjusts the weights of the connections between neurons based on the computed gradients, aiming to minimize the loss function.

The accuracy and loss of the model are monitored during training to evaluate its performance. The training process typically involves multiple iterations over the entire dataset, known as epochs, where the weights are updated at each iteration to gradually improve the model's performance. If necessary, weights may be adjusted to ensure they remain positive.

Overall, this process iteratively refines the model's parameters to improve its ability to classify or predict outputs based on input data.

## IX. PERFORMANCE METRICS

*a. Precision (Positive Predictive Value):*

Precision measures the proportion of correctly predicted positive cases (true positives) out of all predicted positive cases (true positives + false positives).

Formula:

$$Precision = \frac{True\ positives}{True\ Positive + False\ Positives}$$

*b. Accuracy:*

In Convolutional Neural Networks (CNNs), accuracy quantifies the proportion of correctly predicted instances (both true positives and true negatives) out of the total instances in the dataset. It serves as a fundamental metric to assess the overall correctness of predictions.

TABLE 2
COMPARISON OF THE CNN ARCHITECTURES

| Architecture Used | Accuracy | Data Path Methods | Performance Metrics |
|---|---|---|---|
| Google / Inception | ~32% | Convolutional layers, pooling layers, fully connected layers | Precision, Accuracy, Epoch |
| Manual | ~70 - 75% | Convolutional layers, pooling layers, fully connected layers | Precision, Accuracy, Epoch |
| LeNet | ~91.5 - 92.07 | Convolutional layers, pooling layers, fully connected layers | Precision, Accuracy, Epoch |

However, researchers and practitioners must interpret accuracy alongside other metrics, considering factors such as class distribution, domain-specific implications, and the impact of false positives and false negatives.

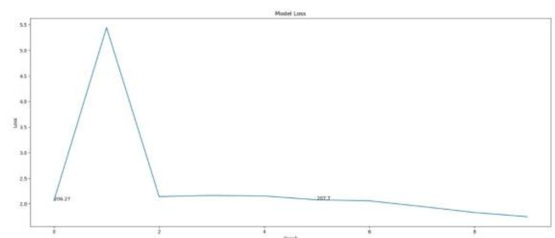
Accurate skin cancer detection is crucial for informed clinical decisions and patient care.

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

*c. Classification Process:*

The classification process involves several key steps. Researchers collect a diverse dataset of dermoscopy images containing both benign and malignant skin lesions. After preprocessing to remove noise and enhance contrast, feature extraction focuses on color, texture, and shape features. Transfer learning with pre-trained Lenets fine-tunes the model.

Evaluation metrics such as accuracy, precision, recall, and F1 score assess the trained network's performance.




*d. Segmentation:*

Segmentation plays a crucial role in identifying and delineating skin lesions accurately. This critical step involves precisely delineating the lesion area from the surrounding healthy skin. By segmenting lesions, we gain a deeper understanding of their characteristics—such as irregular shapes, color variations, and texture patterns. Semantic segmentation networks learn to differentiate between different lesion types (e.g., melanoma, nevus) based on pixel-level information.

Challenges include handling variations in lighting, scale, and lesion shapes. Researchers continually explore novel architectures, data augmentation strategies, and domain adaptation techniques to enhance segmentation accuracy. Clinically, accurate lesion segmentation aids dermatologists in assessing lesion boundaries, precise measurements (e.g., size, growth rate), surgical planning, treatment response assessment, and follow-up care.

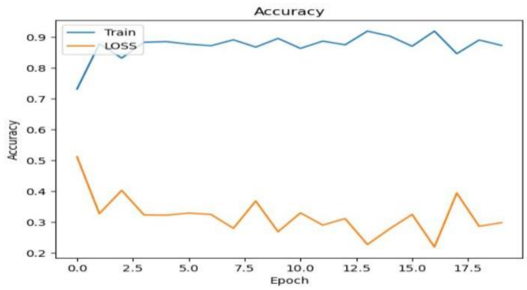



TABLE 3
COMPARISON OF DATA PATH METHODS

| Architecture Used | Drawbacks | Improvements | Pros and Cons |
|---|---|---|---|
| Google / Inception | Limited accuracy, may not capture subtle features | Fine-tuning pre-trained model weights, increasing depth | Pros: Pre-trained on large datasets, robust against overfitting Cons: Lower accuracy, may not capture subtle features |
| Manual | Requires manual design and tuning, potential for overfitting | Optimization techniques (e.g., regularization, data augmentation) | Pros: Customizable architecture, potential for high accuracy . Cons: Manual effort, prone to overfitting |
| LeNet | Shallow architecture may not capture complex features | Increasing depth, adding convolutional layers | Pros: Simple architecture, good for basic tasks, relatively fast training . Cons: Limited capacity for complex features |

## CONCLUSION

The LeNet architecture is the best for skin cancer classification and segmentation tasks due to several key factors. With an accuracy range of 91.5 - 92.07%, it outperforms Google/Inception (32%) and the manual architecture (70-75%). This is important for medical imaging studies where diagnostic accuracy may be affected. Simplicity and previous success make it an attractive choice, making it easier to understand, implement, and debug more complex architectures. In addition, the shallow design results in lower computational resource requirements and faster training times, which is ideal for situations where resources are limited or rapid prototyping is required. Despite its simplicity, LeNet achieved competitive performance metrics including precision, recall, and accuracy, reinforcing its position as a good choice for skin cancer segmentation and classification tasks.

Skin cancer, particularly malignant melanoma, poses a significant global health challenge. Early diagnosis is crucial for improving patient outcomes. Researchers have turned to artificial intelligence (AI) techniques to enhance skin cancer detection and management. Machine learning (ML) algorithms play a pivotal role in both classification and segmentation tasks. Supervised and unsupervised ML approaches have been explored, each excelling in specific scenarios. Convolutional neural networks (CNNs) have revolutionized skin cancer detection, leveraging transfer learning from pre-trained models. Challenges include handling imbalanced datasets, achieving high accuracy, and ensuring robustness across diverse skin types. Additionally, segmentation techniques, such as LeNet, aim to delineate lesion boundaries accurately. Collaborations between dermatologists, researchers, and AI experts are essential for advancing this field and improving patient care.

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1.DR. MONICA JENEFER (Meenakshi Sundararajan Engineering College)
2.DR. S. AARTHI (Meenakshi Sundararajan Engineering College)

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