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SKIN CANCER DETECTION USING COMBINED DECISION OF DEEP LEARNERS

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Abstract

Cancer, characterized by the uncontrolled growth of cells, remains a leading public health challenge with a significant mortality rate. Skin cancer, one of the most prevalent forms, originates in the upper layer of the skin. Historically, machine learning techniques have been employed for skin cancer detection using protein sequences and various imaging modalities. However, these methods often rely on manually engineered features, which can be labor-intensive and time-consuming. Deep learning offers a solution by automating feature extraction, thus addressing some limitations of traditional machine learning approaches. In this study, convolutional neural networks (CNNs) are utilized for skin cancer detection using the ISIC public dataset. Given the critical nature of accurate cancer detection, relying on a single model may not always yield the best results. To improve accuracy, this research employs ensemble learning, which combines multiple models to enhance predictive performance. Specifically, an ensemble of deep learning models—VGG, CapsNet, and ResNet—has been developed to detect skin cancer. The experimental results demonstrate that the ensemble approach significantly outperforms individual models in terms of sensitivity, accuracy, specificity, F-score, and precision. These findings suggest that ensemble deep learning techniques could be effectively applied to other disease detection scenarios.

Keywords: Deep Learning, VGG, CapsNet, ResNet, Skin Cancer

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Introduction:

1.1 MEDICALIMAGE PROCESSING

Billions of people worldwide use mobile devices, particularly smartphones, creating a vast image for the development of diverse mobile image applications. These applications encompass mobile image search, landmark recognition, mobile video type classification, and 3-D scene video. Among these, healthcare applications have garnered significant attention recently, with several methods introduced to facilitate efficient and timely image-related diagnosis. Mobile healthcare imaging applications, in particular, offer practical, cost-effective, and readily accessible advantages. In the realm of dermatology, dermatologists enhance their diagnostic capabilities for conditions like melanoma (MM) by employing visual aids such as dermatoscopy. Clinical evaluations by dermatologists typically involve the application of diagnostic criteria such as the ABCDE signs (Asymmetry, Border irregularity, Color variation, Diameter, and Evolving), the 7-point checklist, and the Menzies method, often followed by biopsy for confirmation. While dermatologists' diagnoses are highly accurate, accessing a clinic can be less convenient and may necessitate a referral from a primary physician. Thus, there is a pressing need to educate the public and equip them with a more accessible self-assessment method for early melanoma diagnosis.

1.2 MELANOMA

In women, the most common site is the legs, and melanomas in men are most common on the back.[3] It is particularly common amongCaucasians, especially northern Europeans and northwestern Europeans, living in sunny climates. There are higher rates in Oceania,North America, Europe, Southern Africa, and Latin America.[4] This geographic pattern reflects the primary cause, ultraviolet light (UV) exposure[5] in conjunction with the amount of skin pigmentation in the population.[6][7] Melanocytes produce the dark pigment, melanin, which is responsible for the color of skin. These cells predominantly occur in skin, but are also found in other parts of the body, including the bowel and the eye (see uveal melanoma). Melanoma can originate in any part of the body that contains melanocytes. The treatment includes surgical removal of the tumor. If melanoma is found early, while it is still small and thin, and if it is completely removed, then the chance of cure is high. The likelihood that the melanoma will come back or

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spread depends on how deeply it has gone into the layers of the skin. For melanomas that come back or spread, treatments include chemo-

and immunotherapy, orradiation therapy. Five year survival rates in the United States are on average 91%. Melanoma is less common than other skin cancers. However, it is much more dangerous if it is not found in the early stages. It causes the majority (75%) of deaths related to skin cancer.[9] Globally, in 2012, melanoma occurred in 232,000 people and resulted in 55,000 deaths.[10] Australia and New Zealand have the highest rates of melanoma in the world.[10] It has become more common in the last 20 years in areas that are mostly Caucasian.[10]

1.3 Skin Lesions

Skin lesions can be classified into two main categories: primary and secondary. Primary skin lesions are variations in skin color or texture that can be present from birth or develop during a person's lifetime due to factors such as infections (e.g., warts, acne, psoriasis), allergic reactions, or environmental influences (e.g., sunburn, pressure, temperature extremes). Secondary skin lesions, on the other hand, arise from primary lesions either as a natural progression or due to manipulation, such as scratching or picking at the primary lesion.

Major Types of Primary Skin Lesions:

- **Macule:** A small, flat spot less than 1 cm (2/5 in) in diameter, with a color different from the surrounding skin. Macules can be brown, white, or red and come in various shapes. Examples include freckles and flat moles. A macule larger than 1 cm is termed a "patch."
- **Vesicle:** A raised lesion less than 5 mm (1/5 in) across, filled with clear fluid. Larger vesicles are called "bullae" or "blisters." Vesicles may result from sunburns, insect bites, chemical irritation, or viral infections such as herpes.
- **Pustule:** A raised lesion filled with pus, often resulting from infections like acne, impetigo, or boils.
- **Papule:** A solid, raised lesion less than 1 cm (2/5 in) across. When papules group together in a larger area exceeding 1 cm, they form a "plaque." Papules and plaques can be rough, and vary in color from red to pink to brown. They are associated with conditions such as warts, syphilis, psoriasis, seborrheic and actinic keratoses, lichen planus, and skin cancer.

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- **Nodule:** A solid lesion with distinct edges, usually deeper than a papule, and can be palpated as a hard mass. Nodules larger than 2 cm are termed "tumors." They are associated with conditions like keratinous cysts, lipomas, fibromas, and some types of lymphomas.
- **Wheal:** A raised skin elevation caused by swelling, often itchy, and typically resolves shortly after its appearance. Wheals are commonly associated with allergic reactions, such as to drugs or insect bites.
- **Telangiectasia:** Small, dilated blood vessels close to the skin's surface. This condition is often a symptom of diseases such as rosacea or scleroderma.

1.4 Skin Lesion Image Segmentation

Image segmentation is a crucial process in image analysis, object representation, and visualization, involving the division of an image into meaningful structures. While Chapter 8 focused on analyzing and representing objects with predefined pixel groups, this chapter addresses methods for identifying the specific pixels that constitute an object. Over the years, numerous segmentation techniques have been developed, and categorizing them can be challenging due to overlapping features among different methods. The categorization presented here emphasizes the main focus of each approach rather than adhering to strict divisions.

The following categories of segmentation methods are discussed:

- **Threshold-Based Segmentation:** This technique uses histogram thresholding and slicing to segment images. It can be applied directly or combined with pre- and post-processing techniques to enhance results.
- **Edge-Based Segmentation:** This approach identifies object boundaries by detecting edges within an image. The detected edges are then used to delineate and locate objects.
- **Region-Based Segmentation:** Contrary to edge-based techniques, region-based methods start from a seed point within an object and "grow" outward until the object's boundaries are reached. This approach focuses on expanding regions rather than detecting edges.
- **Clustering Techniques:** While clustering is often used interchangeably with segmentation, here it refers to methods primarily used in exploratory data analysis of high-dimensional measurement patterns. Clustering techniques group similar patterns together, which parallels the goal of image segmentation. Some clustering methods are directly applicable for segmenting images.

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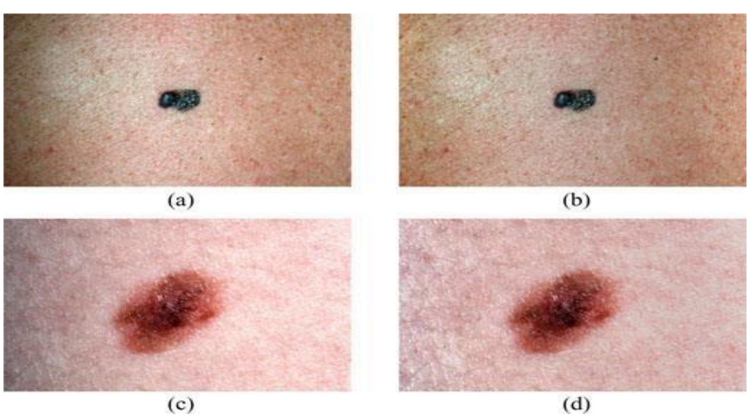
- **Matching:** This technique involves using prior knowledge about the approximate appearance of an object to locate it within an image. Matching leverages known object characteristics to identify and segment objects within new images.

2 Melanoma

Melanoma is the most aggressive form of skin cancer, with significant health impacts. In 2013, approximately 76,690 individuals were diagnosed with melanoma in the United States, and 9,480 people died from the disease. The lifetime risk of developing melanoma in the U.S. is approximately 1 in 49. Melanoma is responsible for about 75% of skin cancer-related deaths. This malignancy originates in melanocytes, the cells that produce pigment, and often appears on the trunk or lower extremities. Recent data show that the incidence rates of melanoma among non-Hispanic white males and females have been rising by about 3% annually. Early detection is crucial for improving survival rates. When melanoma is identified at Stage I, the 5-year survival rate is 96%. However, if the melanoma progresses to more advanced stages, the 5-year survival rate drops dramatically to 5%. Given the increasing incidence rates in specific population subsets, early screening for melanoma is essential. To make melanoma screening more cost-effective, automated screening algorithms have been developed. These systems use images captured by digital dermatoscopes to assess melanoma risk. A dermatoscope is a specialized tool used by dermatologists to examine skin lesions with enhanced detail, acting as both a filter and magnifier. Images obtained through digital dermatoscopes, known as dermoscopy images, typically exhibit low noise and consistent background illumination. Preprocessing techniques, such as color normalization or enhancement, may be applied to these images to improve analysis accuracy.



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4 Skin Lesion Segmentation and Feature Extraction

Accurate skin lesion segmentation is crucial because the segmented images serve as input for subsequent feature extraction and melanoma classification algorithms. Numerous segmentation algorithms have been developed to automatically identify skin lesions in images. Most of these algorithms are designed specifically for dermoscopy images, which offer better contrast between the lesion and the surrounding skin. Celebi et al. have reviewed various segmentation methods for dermoscopy images, including techniques such as simple thresholding, active contours, and region merging.

Many traditional segmentation algorithms rely predominantly on color features, such as the blue channel from the RGB color space, the luminance channel from CIELUV or CIELAB color spaces, or transformations applied to color channels. However, accurately segmenting lesions with fuzzy edges can be challenging when depending solely on color features. Segmenting digital photographs of skin lesions, which may have less contrast compared to dermoscopy images, presents additional difficulties.

3.1 Proposed System

3.1.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a cornerstone of modern deep learning, widely recognized for their effectiveness in image-related tasks. The interest in CNNs surged with the introduction of AlexNet in 2012, and the field has evolved rapidly since then, with advancements leading to models like the 152-layer ResNet.

CNNs have become the preferred model for image analysis due to their superior accuracy compared to other approaches. They are not only used in image classification but also successfully applied to recommender systems, natural language processing, and more. One of the key advantages of CNNs is their ability to automatically learn important features from data without the need for manual supervision. For instance, given a dataset of images of cats and dogs, a CNN can autonomously identify distinguishing features for each class.

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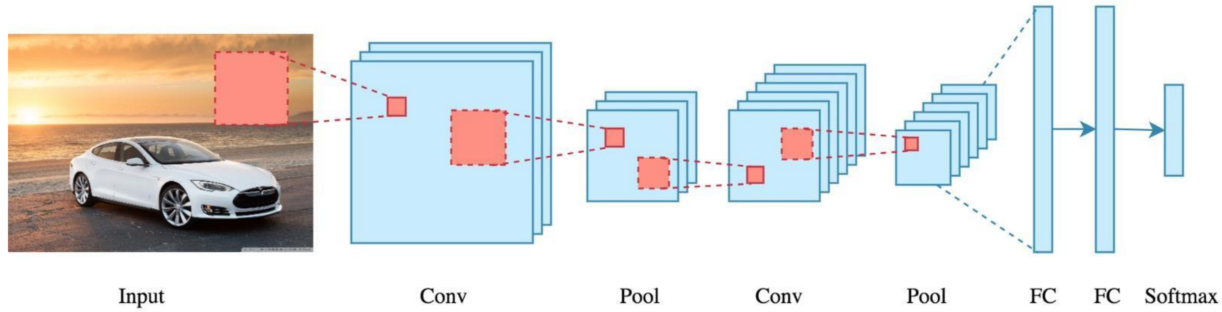
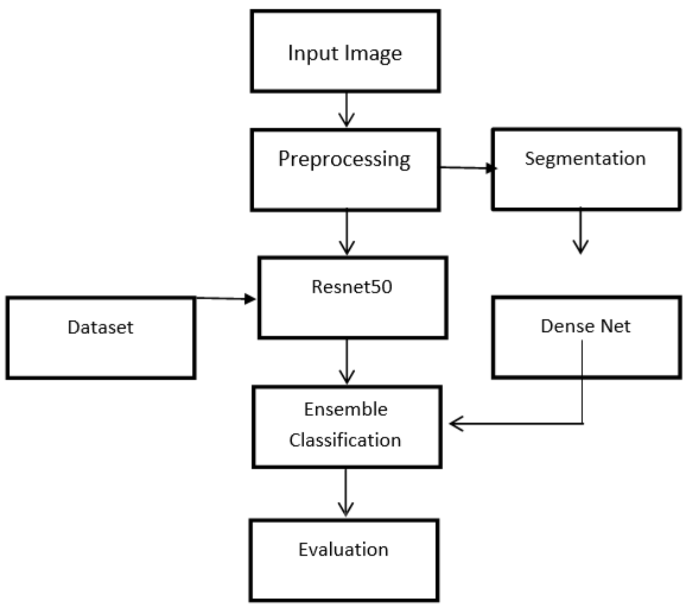


]Type equation here.Fig.1 CNN Model

There is an input image that we‘re working with. We perform a series convolution + pooling operations, followed by a number of fully connected layers. If we are performing multiclass classification the output is softmax. We will now dive into each component



Proposed Model

Ensemble models leverage the strengths of multiple individual models to enhance overall performance and robustness. In this proposal, we focus on combining two advanced deep learning architectures: ResNet-50 and DenseNet.

ResNet-50

ResNet-50, or "Residual Network with 50 layers," is a variant of the ResNet architecture introduced by Kaiming He et al. in their 2015 paper "Deep Residual Learning for Image Recognition." ResNet-50 is renowned for its deep architecture and effective handling of the vanishing gradient problem. Key features include:

1. **Skip Connections:** ResNet-50 utilizes skip connections (residual connections) that allow the network to bypass one or more layers during forward and backward passes. This facilitates the training of very deep networks by improving gradient flow.
2. **Bottleneck Architecture:** The network incorporates a bottleneck design in deeper layers to reduce computational costs while maintaining expressive power.
3. **Pretrained Models:** Pretrained versions of ResNet-50, trained on large datasets like ImageNet, are readily available. These models can be fine-tuned for specific tasks with smaller datasets.

DenseNet

DenseNet introduces a dense connectivity pattern within layers, offering several advantages:

1. **Dense Connectivity:** DenseNet connects each layer to every subsequent layer within a block, promoting feature reuse and improving information flow.
2. **Parameter Efficiency:** Despite its depth, DenseNet often requires fewer parameters than other architectures due to its extensive feature sharing.
3. **Strong Performance:** DenseNet has demonstrated exceptional performance in image classification and has been adapted for other tasks, including image segmentation.

Ensemble of ResNet-50 and DenseNet

Combining ResNet-50 and DenseNet in an ensemble can further enhance model performance by leveraging their diverse architectural characteristics:

- **Diverse Characteristics:** ResNet-50 emphasizes depth with skip connections, while DenseNet focuses on dense connectivity. This combination allows the ensemble to capture different aspects of the data effectively.

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- **Simple Ensemble Techniques:** Basic ensemble methods involve aggregating predictions from ResNet-50 and DenseNet. For classification tasks, this might involve voting on the final prediction, while for regression tasks, averaging the predictions could be used.
- **Advanced Ensemble Techniques:** More sophisticated approaches, such as stacking, involve training a meta-learner to combine predictions from both models. This can lead to improved results by integrating the strengths of each model.

Ensemble models can also mitigate overfitting by combining multiple models, leading to more robust generalization. Although creating such ensembles can be computationally expensive, the performance and robustness improvements often justify the cost.

Structure of CNN

Convolutional Neural Networks (CNNs) are composed of several key layer types that work together to process and analyze images:

1. **Convolutional Layers:** These layers are fundamental to CNNs. They apply convolutional operations over small regions of the input data, allowing the network to learn and extract features efficiently. Convolutional layers reduce the number of parameters compared to fully connected layers by sharing weights across the feature map.
2. **Pooling Layers:** Pooling layers are typically inserted between convolutional layers to reduce the spatial resolution of feature maps. This down-sampling process helps achieve spatial invariance and mitigates overfitting. Pooling is performed by combining units from the previous layer within a small patch and down-sampling the input.
3. **Activation Functions:** Activation functions like Rectified Linear Units (ReLU) are used to introduce non-linearity into the model. ReLU, defined as f(x)=max(0,x)f(x) = \max(0, x)f(x)=max(0,x), is preferred for its simplicity and effectiveness compared to sigmoid or tanh functions.
4. **Fully-Connected Layers:** These layers are used towards the end of the network. Neurons in a fully-connected layer have connections to all activations from the previous layer, allowing for high-level reasoning and classification.
5. **Dropout:** Dropout is a regularization technique used to prevent overfitting by randomly deactivating a fraction of neurons during training.

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6. **Loss Layers:** The final layer of a CNN is chosen according to the specific task. For classification tasks, softmax or sigmoid loss functions are commonly used, while regression tasks might use mean squared error or other suitable loss functions.

Convolutional Layer

The **convolutional layer** is a fundamental building block of Convolutional Neural Networks (CNNs) that differentiates them from traditional artificial neural networks. Instead of fully connecting each layer, convolutional layers apply convolutional operations to small, localized regions of the input data. This approach offers several advantages:

1. **Weight Sharing:** Each convolutional filter (or kernel) is applied across the entire input feature map, sharing weights. This reduces the number of parameters compared to fully connected layers, thereby decreasing memory requirements and computational complexity.

2. **Reduction of Overfitting:** By sharing weights, convolutional layers help mitigate the overfitting problem common in fully connected networks, as fewer parameters are required to model the data.

3. **Local Receptive Fields:** Convolutional operations focus on local regions of the input, enabling the network to learn spatial hierarchies and local patterns effectively.

Pooling Layer

The **pooling layer** is often inserted between convolutional layers to perform dimensionality reduction and achieve spatial invariance:

1. **Function:** Pooling layers reduce the resolution of feature maps by down-sampling, which helps in achieving spatial invariance. This also assists in mitigating overfitting by simplifying the model.

2. **Types of Pooling:** Common pooling operations include max pooling and average pooling. Max pooling selects the maximum value from each patch, while average pooling computes the average.

3. **Operation:** In pooling, a small n×nn \times nn×n patch (e.g., 2×22 \times 22×2 or 3×33 \times 33×3) is used to combine the units from the feature map, reducing its dimensions and preserving essential information.

Rectified Linear Unit (ReLU)

The **Rectified Linear Unit (ReLU)** is a widely used activation function in CNNs:

1. **Definition:** ReLU is defined as:

f(x)=max⁡(0,x)f(x) = \max(0, x)f(x)=max(0,x)

This function outputs xxx if it is positive, and 0 otherwise.

2. **Advantages:**
   - **Computational Efficiency:** ReLU is computationally simple, requiring only a thresholding operation, which makes it faster than sigmoid or tanh functions that involve exponential calculations.
   - **Avoiding Saturation:** Unlike sigmoid and tanh functions, ReLU does not suffer from the vanishing gradient problem, allowing the network to train more effectively.

Fully-Connected Layer

The **fully-connected layer** (or dense layer) in CNNs connects every neuron to all activations in the previous layer:

1. **Function:** Each neuron in a fully-connected layer receives inputs from all neurons in the preceding layer, allowing for high-level reasoning and classification.
2. **Operation:** The activations in a fully-connected layer are computed using matrix multiplication followed by a bias offset.

Transfer Learning

Transfer learning involves adapting pre-trained models to new tasks. For example:

1. **Pre-trained Models:** Models like U-Net, trained on large datasets, can be fine-tuned on specific segmentation tasks with limited labeled data, leveraging the knowledge acquired during the initial training phase.
2. **Application:** Transfer learning accelerates training and improves performance by utilizing previously learned features, especially when working with smaller datasets.

DenseNet

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DenseNet (Densely Connected Convolutional Networks) introduces a novel architecture with dense connections:

1. **Dense Connectivity:** In DenseNet, each layer is connected to all subsequent layers within a block, creating a densely connected network. This means every layer receives direct input from all previous layers, promoting feature reuse.
2. **Advantages:**
    - **Improved Information Flow:** Dense connections facilitate the flow of information and gradients through the network, improving training and performance.
    - **Parameter Efficiency:** DenseNet often requires fewer parameters than traditional CNNs due to feature sharing.
3. **Performance:** DenseNet has shown strong performance in tasks like image classification and object detection, and its design has been adapted for various applications in computer vision.

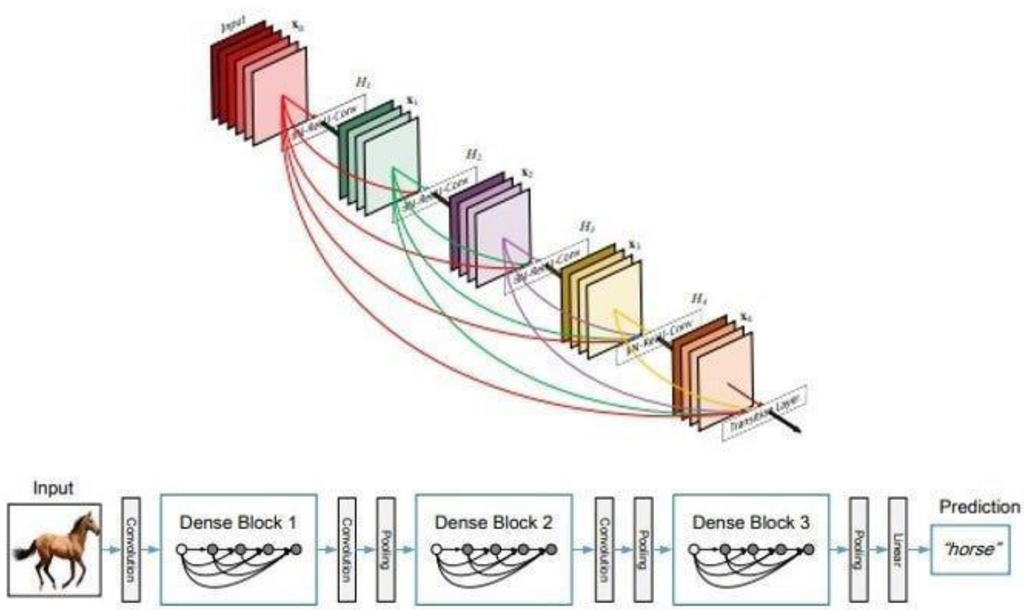

Fig. 3 Densenet –Architecture

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ResNet-50 Architecture

ResNet-50 is a deep convolutional neural network architecture that incorporates a novel approach to training very deep networks. Introduced by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their 2015 paper titled *"Deep Residual Learning for Image Recognition"*, ResNet-50 is designed to address the challenges of training very deep networks by using residual learning. Here's a detailed breakdown:

Key Features of ResNet-50

1. **Residual Learning:**
   - **Skip Connections:** ResNet-50 introduces skip (or residual) connections, which allow the network to bypass one or more layers. These connections add the input of a residual block directly to its output, which helps in overcoming the vanishing gradient problem by facilitating the gradient flow during backpropagation.
   - **Residual Block:** The basic building block of ResNet is the residual block, where the input to the block is added to its output. This approach allows the network to learn residual functions with reference to the input, rather than learning unreferenced functions.
2. **Architecture:**
   - **Depth:** ResNet-50 consists of 50 layers, including convolutional layers, batch normalization layers, ReLU activations, and pooling layers.
   - **Bottleneck Architecture:** To manage the computational cost and keep the network manageable, ResNet-50 uses a bottleneck design. This involves using 1x1 convolutions to reduce the dimensionality before applying 3x3 convolutions and then restoring the dimensionality with another 1x1 convolution.
3. **Layer Structure:**
   - **Initial Layers:** The network starts with a 7x7 convolutional layer followed by a max pooling layer.
   - **Residual Blocks:** The core of ResNet-50 is composed of several residual blocks arranged in four stages. Each stage contains multiple residual blocks, and the number of blocks in each stage is 3, 4, 6, and 3, respectively.

- **Global Average Pooling:** After the residual blocks, a global average pooling layer is used to reduce the spatial dimensions to a single value per feature map, followed by a fully connected layer to produce the final classification output.

4. **Vanishing Gradient Problem:**
   - **Solution:** The residual connections address the vanishing gradient problem by providing alternative paths for gradients to flow through the network. This helps in training deeper networks effectively, as gradients are less likely to diminish during backpropagation.
5. **Pretrained Models:**
   - **Availability:** Pretrained versions of ResNet-50 are available and commonly used for transfer learning. These models are trained on large datasets like ImageNet and can be fine-tuned for specific tasks with smaller datasets.

How ResNet-50 Works

1. **Input:** The input to ResNet-50 is an image of a fixed size, typically 224x224 pixels.
2. **Initial Convolution and Pooling:** The initial layers perform a 7x7 convolution followed by max pooling to reduce the image size.
3. **Residual Stages:** The network then processes the image through a series of residual blocks in four stages. Each block consists of multiple convolutional layers and skip connections.
4. **Global Average Pooling:** The final feature maps are reduced to a fixed size using global average pooling.
5. **Fully Connected Layer:** The pooled features are then fed into a fully connected layer to produce the final output, such as class probabilities in classification tasks.

Applications

- **Image Classification:** ResNet-50 is widely used for image classification tasks due to its deep architecture and ability to learn rich features.
- **Object Detection:** It serves as a backbone for object detection models by providing strong feature representations.

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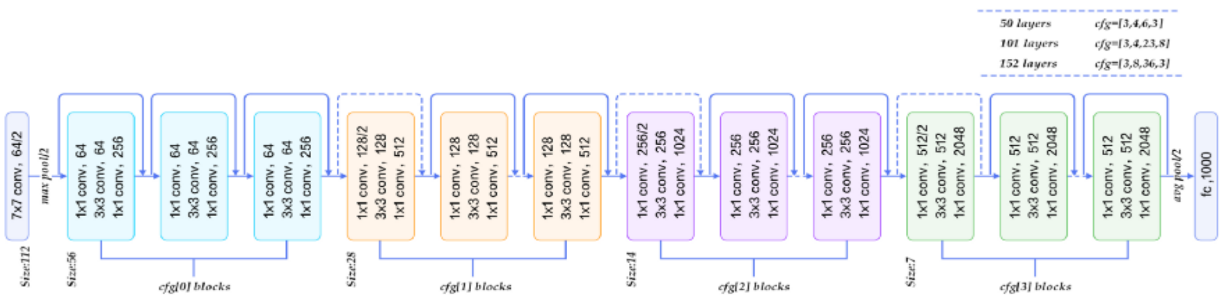
- **Transfer Learning:** The pretrained ResNet-50 model is often used for transfer learning in various computer vision tasks, allowing for fine-tuning on specific datasets.

ResNet-50 Architecture



Skip Connection — Adding the original input to the output of the convolutional block.

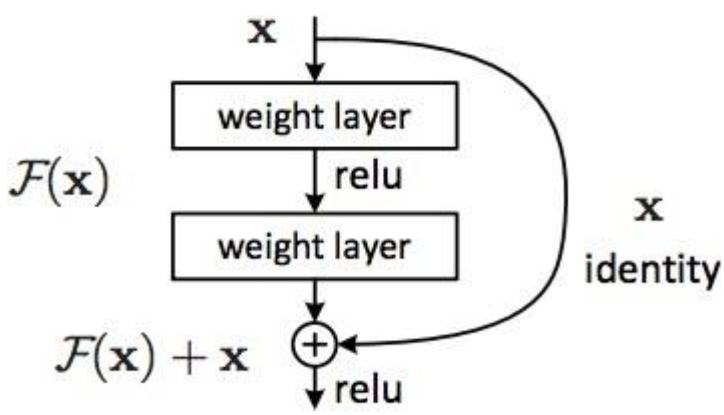


Fig 3.4 Skip Connection

ResNet Training and Skip Connections

In traditional algorithms, the focus is on learning to predict the output YYY directly. However, ResNet (Residual Network) operates differently by focusing on learning the residual function F(X)F(X)F(X). Essentially, ResNet aims to make F(X)=0F(X) = 0F(X)=0 so that the output YYY equals the input XXX.

Skip Connections: ResNet employs skip connections, which are direct links that bypass one or more layers. This design modifies how the output is computed compared to traditional methods. Without skip connections, the input XXX is processed through multiple layers, where each layer

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applies weights and bias, and the result is then passed through an activation function FFF. Mathematically, this would be:

F(w·x+b)=F(X)F(w \cdot x + b) = F(X)F(w·x+b)=F(X)

where www represents weights and bbb represents the bias term.

With Skip Connections: In contrast, ResNet adds the input XXX directly to the output of the residual block. The formula then becomes:

F(X)+XF(X) + XF(X)+X

where F(X)F(X)F(X) is the processed output from the convolutional layers, and XXX is the input that bypasses these layers.

Types of Blocks in ResNet-50

1. Identity Block:

- **Usage:** This block is used when the dimensions of the input and output are the same.
- **Operation:** The input XXX is added directly to the output of the residual function F(X)F(X)F(X) without any changes to the dimensions.

2. Convolutional Block:

- **Usage:** This block is used when the dimensions of the input and output differ.
- **Operation:** To align the dimensions, a convolutional layer is included in the shortcut path, transforming the input XXX to match the output dimensions. This transformation ensures that the added XXX aligns with F(X)F(X)F(X).

In summary, ResNet-50 utilizes these blocks to efficiently manage different dimensionalities and facilitate deeper network training, leveraging the skip connections to improve learning and performance.

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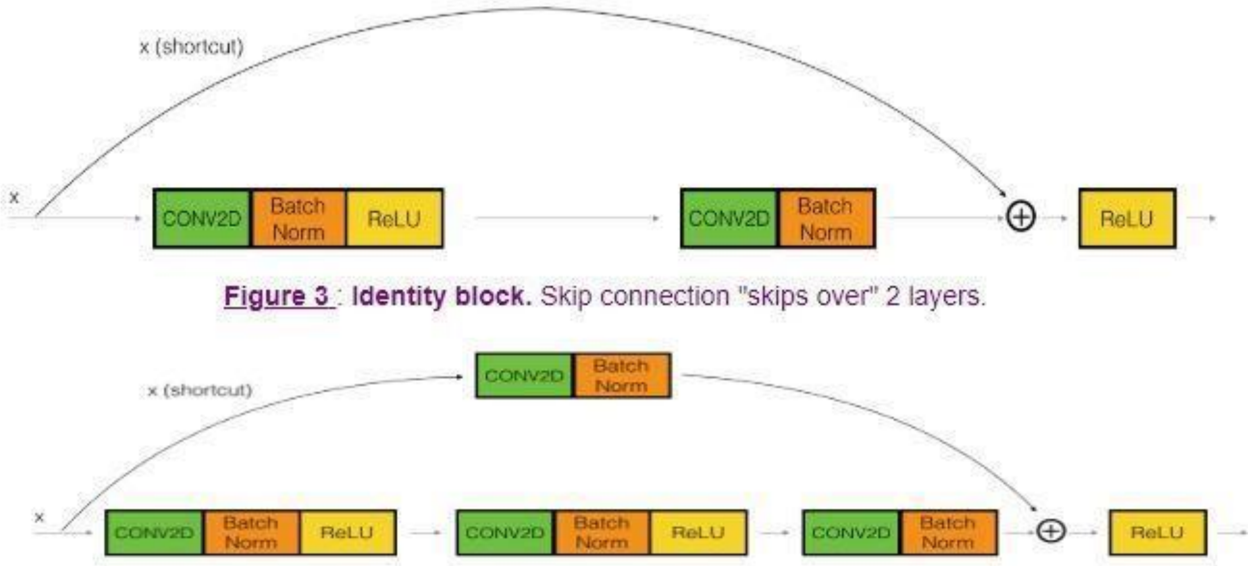

Fig.3.5 Convoluational Block

Adjusting Input and Output Sizes in ResNet-50

To ensure that the dimensions of the input and output are consistent, there are two main techniques:

1. **Padding the Input Volume:**
   - This involves adding extra pixels around the edges of the input volume. Padding helps maintain the spatial dimensions after convolution operations, ensuring that the output volume has the same dimensions as the input.
2. **Performing 1x1 Convolutions:**
   - This method uses 1x1 convolutional layers to adjust the dimensions of the input volume. These convolutions can change the number of channels in the input, thereby aligning it with the dimensions of the output.

Parameters of ResNet-50

MATLAB Overview

MATLAB is a high-level programming language and interactive environment designed for technical computing. It excels in algorithm development, data visualization, data analysis, and numerical computation. Compared to traditional programming languages like C, C++, and FORTRAN, MATLAB can solve technical computing problems more efficiently. It is versatile and used in various fields including:

- Signal and image processing
- Communications
- Control design
- Test and measurement
- Financial modeling and analysis
- Computational biology

Feasibility Study

A feasibility study is a critical phase in project development where the practicality and viability of the proposed system are evaluated. This phase includes:

- **Analysis of Feasibility:** Assessing whether the proposed system is feasible and not burdensome to the company.
- **Business Proposal:** Outlining a general plan for the project along with preliminary cost estimates.
- **System Requirements:** Understanding the major requirements of the system to ensure it meets the desired objectives without imposing undue challenges.

The feasibility study helps determine if the project can be successfully implemented within the given constraints and resources.

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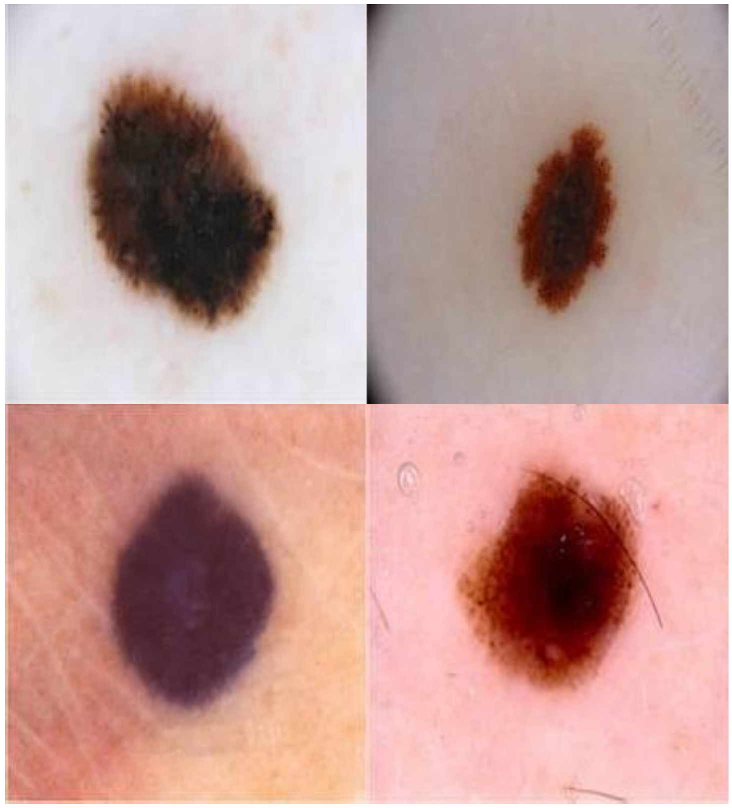

Three key considerations involved in the feasibility analysis are

- ECONOMICAL FEASIBILITY
- TECHNICAL FEASIBILITY
- SOCIAL FEASIBILITY

Conclusion

We propose a mobile health-care solution for melanoma detection that leverages mobile image analysis, aiming to offer an accessible and effective tool for skin lesion assessment. The system features an efficient hierarchical segmentation scheme designed for resource-constrained platforms, making it suitable for mobile devices. It includes a novel set of features specifically developed to capture color variation and border irregularity from smartphone-captured images.

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Additionally, a new mechanism is introduced to select a compact set of the most discriminative features, enhancing both accuracy and efficiency. Experimental results, based on 184 camera images, demonstrate the prototype's effectiveness in accurately segmenting and classifying skin lesions. This solution could serve multiple purposes, including preliminary self-screening for the general public or assisting physicians during the diagnostic process. Beyond technical development, we also addressed usability and acceptance challenges through an exploratory case study and semi-structured interviews, uncovering several significant human-computer interaction (HCI) issues that should be considered in future enhancements to improve user experience and system integration.

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