

# Good morning, everyone!

---

Today, we are excited to share with you the application of ResNet in skin disease diagnosis and how deep learning is revolutionizing the field of medical imaging.

## Background of Skin Disease Diagnosis

---

Skin disease diagnosis is a challenging task due to the variability and complexity of skin lesions. Different skin conditions can have similar symptoms, and lesions can vary in size, shape, color, and texture. Early and accurate diagnosis is crucial for effective treatment and management of skin diseases. However, manual diagnosis by dermatologists can be subjective and error-prone, which is why there is a need for more reliable methods. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown promise in automating and improving the accuracy of skin disease diagnosis.

## Why Introduce ResNet?

---

So, why do we need ResNet? ResNet, or Residual Network, is a type of deep convolutional neural network introduced by Kaiming He et al. in 2015. It addresses several key issues that arise in deep neural networks, such as the vanishing gradient problem and overfitting.

One of the main problems in deep networks is overfitting. Overfitting occurs when a model performs well on training data but poorly on unseen test data. This happens because the model memorizes the training data rather than learning to generalize. For example, consider a deep CNN trained on a small dataset. As the network gets deeper, it might start to overfit, meaning it performs well on the training data but fails to generalize to new data.

## Vanishing Gradient Problem

---

Another critical issue in deep networks is the vanishing gradient problem. In deep networks, gradients can become so small during back propagation that they effectively vanish, making it difficult to train the network. As the network depth increases, the training process becomes unstable, and the model's performance degrades.

To illustrate this, let's look at the gradient of the loss function  $L$  with respect to the input  $x$  for a three-layer neural network:

$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial a^3} \cdot \frac{\partial a^3}{\partial z^3} \cdot \frac{\partial z^3}{\partial a^2} \cdot \frac{\partial a^2}{\partial z^2} \cdot \frac{\partial z^2}{\partial a^1} \cdot \frac{\partial a^1}{\partial z^1} \cdot \frac{\partial z^1}{\partial x}$$

Expanding this, we get:

$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial a^3} \cdot f'(z^3) \cdot w^3 \cdot f'(z^2) \cdot w^2 \cdot f'(z^1) \cdot w^1$$

If the derivatives of the activation functions  $f'(z^l)$  are very small (for example, for the sigmoid function,  $f'(z)$  ranges between 0 and 0.25), then the product of these small values can result in an overall gradient that is very close to zero. This is known as the vanishing gradient problem.

# ResNet Architecture Explained - Basic Concepts

---

Now, let's dive into the architecture of ResNet. The key innovation in ResNet is the introduction of skip connections, also known as residual connections. These connections allow the network to learn residual functions with reference to the layer inputs, instead of learning unreferenced functions.

## Forward and Backward Propagation in ResNet

---

Let's now look at how forward and backward propagation work in ResNet.

### Forward Propagation

The feature  $x_L$  of any deeper unit  $L$  can be represented as the sum of the input feature  $x_l$  of any shallower unit  $l$  and the outputs of all intermediate residual functions:

$$x_L = x_l + \sum_{i=l}^{L-1} \mathcal{F}(x_i, W_i)$$

### Backward Propagation

The gradient  $\frac{\partial E}{\partial x_l}$  can be decomposed into two terms: a direct term that propagates information without concerning any weight layers, and another term that propagates through the weight layers:

$$\frac{\partial E}{\partial x_l} = \frac{\partial E}{\partial x_L} \left( 1 + \sum_{i=l}^{L-1} \frac{\partial \mathcal{F}(x_i, W_i)}{\partial x_l} \right)$$

## How ResNet Solves the Problem and Performance Data

---

So, how does ResNet solve these problems? The skip connections in ResNet help alleviate the vanishing gradient problem by providing a direct path for gradient flow. This means that even in very deep networks, the gradients can still propagate effectively, allowing the network to be trained more efficiently.

ResNet has shown significant improvements over traditional CNNs in various tasks, including skin disease diagnosis. Let's look at some performance data:

- **Dataset:** ISIC (International Skin Imaging Collaboration) dataset, containing thousands of dermoscopic images.
- **Accuracy:** ResNet achieved an accuracy of 95% on the ISIC dataset.
- **Sensitivity:** 93%
- **Specificity:** 97%

When compared to traditional methods, which typically achieve an accuracy around 85-90%, ResNet shows a significant improvement in both accuracy and generalization.

# Future Applications of ResNet

---

The success of ResNet in skin disease diagnosis opens up numerous future applications. In medical imaging, ResNet can be used for detection and segmentation tasks, improving diagnosis and treatment planning. In autonomous driving, ResNet can enhance object recognition and scene understanding, leading to safer and more reliable vehicles.

Additionally, ResNet has potential applications in other domains, such as natural language processing and audio recognition.

## Conclusion

---

In conclusion, ResNet has revolutionized the field of deep learning by addressing key challenges such as the vanishing gradient problem and overfitting. Its ability to train very deep networks has led to significant improvements in various applications, including skin disease diagnosis. We encourage you to explore the potential of ResNet in your own projects and research. The possibilities are endless!

Thank you for your attention. We would be happy to answer any questions you may have.

**Thank you again for joining us today. We hope you found this presentation informative and inspiring.**