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Nail Disease Classification Using Graph Attention Network (GAT) and Resnet

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Abstract: Nail diseases can serve as critical indicators of systemic health issues, making their early detection and classification essential for effective diagnosis and treatment. This study integrates deep learning and graph-based learning to classify nail diseases, utilizing ResNet for feature extraction and Graph Neural Networks (GNNs) for relational learning. A dataset comprising multiple nail disease categories, including Acral Lentiginous Melanoma, Onychogryphosis, Clubbing, Pitting, Blue Finger, and Healthy Nails, was utilized. The ResNet model extracts meaningful feature representations, which are then structured as a graph to capture inter-class relationships using a Graph Attention Network (GAT). Cosine similarity is employed to construct the graph edges to improve connectivity between samples, ensuring that nodes with high feature similarity are more likely to be connected. This approach enhances learning by leveraging relationships between visually similar nail disease patterns. Experimental results demonstrate high classification performance, achieving an accuracy of 0.8791 (88%). This research highlights the effectiveness of combining deep learning with graph-based learning for automated nail disease classification, paving the way for more robust AI-assisted diagnostic tools in dermatology.

Keywords: Nail diseases, ResNet, Graph Neural Network, Classification.

INTRODUCTION

Although often overlooked, nails play a significant role in social interactions. Their appearance, health, and grooming can influence how others perceive us and impact our confidence in social and professional settings. Nails are closely tied to social interaction in several ways: (1) they serve as an indicator of personal hygiene and grooming, which can create positive impressions; (2) they hold cultural and social significance, often symbolizing beauty and status in various cultures; (3) they act as a form of self-expression, with nail art and polish choices reflecting personality, mood, and creativity; and (4) they can have psychological and social effects, as nail disorders may cause embarrassment, reduce self-confidence, and lead to social anxiety or unnecessary social exclusion. So clearly, nails are more than just biological features, they are a vital aspect of personal identity and social communication.

Nail diseases, also called onychopathies, encompass a wide range of conditions that affect the appearance, integrity, and function of fingernails and toenails. These disorders can result from infections, diseases, trauma, or congenital anomalies. Nail diseases, such as fungal infections, psoriasis, melanoma, and onychomycosis, are common health concerns that can indicate underlying medical conditions. Early and accurate diagnosis is crucial for effective treatment. Traditional nail disease diagnosis relies on dermatologists' expertise, but deep learning has emerged as a powerful tool for automating and improving classification accuracy.

Recent advancements in deep learning have significantly enhanced the classification and diagnosis of nail diseases. Several studies have explored various methodologies to improve accuracy and efficiency in this domain such as a study by Shandilya et al (Shandilya et al., 2024) introduced a novel deep learning algorithm employing a hybrid Capsule Convolutional Neural Network (CNN) to autonomously categorize six types of nail disorders, including Blue Finger, Clubbing, Pitting, Onychogryphosis, Acral Lentiginous Melanoma, and Healthy Nails. Capsule Networks offer improved spatial hierarchy learning, leading to better diagnostic accuracy. The use of Capsule Networks helps retain spatial relationships between features, reducing the issue of misclassification common in traditional CNNs. However, the study lacks large-scale datasets, which may limit its generalizability. Senar et.al (Yamac et al., 2022) focused on detecting five different nail diseases using six different deep-learning models on color nail images between conditions such as onychomycosis and nail psoriasis. This study provides an important benchmark by comparing multiple deep learning architectures, but it does not explore the impact of additional preprocessing techniques, such as contrast enhancement, which could further improve classification accuracy. Hamim et al. (Hamim et al., 2023) combined image processing techniques with deep learning models such as MobileNetV2, VGG16, and VGG19 to classify diseased nails. The highest accuracy of 92% was achieved using MobileNetV2. The application of transfer learning proves effective in feature extraction and classification. However, the study does not address class imbalance issues, which may affect the model’s generalization ability across all disease categories. Dalia et.al (Alzahrani et al., 2023) proposed A Deep Hybrid Learning (DHL) model that integrates deep learning for feature extraction with machine learning classifiers for final classification. This method is advantageous because it combines deep learning’s ability to extract hierarchical features with the interpretability of traditional machine learning. However, computational complexity remains a challenge. Yilmaz et al. (Yilmaz et al., 2022) developed a deep neural network model using VGG16 and InceptionV3, achieving accuracy rates of 95.98% and 95.90%, respectively, in detecting fungal infections. The study’s high accuracy rates demonstrate the effectiveness of CNNs for medical image classification. However, the reliance on grayscale images might limit applicability in real-world scenarios where diverse lighting conditions exist. Despite these advancements, challenges such as limited dataset availability, class imbalance, and model interpretability remain.

Graph Neural Networks (GNNs) excel at modeling complex relationships within data, capturing dependencies that traditional methods often miss (Wu et al., 2021). By leveraging graph-based learning, we can create graphs that represent the spatial and textural relationships within nail images. In this framework, nodes represent image features, while edges denote relationships or similarities between these features. This approach allows the model to aggregate contextual information, enhancing classification performance (Kipf & Welling, 2017). Additionally, GNNs can improve the model's ability to distinguish between conditions with similar visual characteristics, ultimately boosting diagnostic accuracy. As a result, the integration of graph-based learning into nail disease classification holds significant promise.

METHOD & MATERIAL

NAIL DISEASE

Nail diseases, or onychopathies, encompass a wide range of conditions affecting the nail unit, including the nail plate, nail bed, matrix, and surrounding tissues. They often serve as indicators of underlying health issues such as psoriasis, diabetes, or cardiovascular diseases. Common nail diseases as shown in Figure 1. Below include onychomycosis (fungal nail infection), characterized by thickening, discoloration, and brittleness; psoriatic nail disease, which presents with pitting, onycholysis, and subungual hyperkeratosis; and paronychia, an infection or inflammation of the nail fold("DermNet," 2025). Other conditions, such as brittle nail syndrome, ingrown toenails, and Beau's lines, further highlight the diversity of nail pathologies.

Figure 1. Variants of Nail Disease
Source: Research Data

Diagnosis typically involves clinical examination, KOH preparation, fungal cultures, and sometimes nail biopsies or blood tests to identify systemic causes. Treatment varies based on the condition and may include antifungal medications, topical corticosteroids, antibiotics, surgical intervention, or nutritional supplementation. Nail diseases not only cause physical discomfort but also significantly impact the quality of life, leading to psychological distress and social anxiety due to their visible nature. Early diagnosis and appropriate management are crucial to prevent complications and improve patient outcomes. According to Gupta et al.(Gupta et al., 2020), onychomycosis remains one of the most challenging nail disorders to treat, requiring prolonged antifungal therapy. Advances in diagnostic tools and therapies continue to enhance the management of nail diseases, underscoring the need for a multidisciplinary approach involving dermatologists, podiatrists, and primary care physicians.

GRAPH ATTENTION NETWORK (GAT)

Graph Attention Networks (GATs) are a type of graph neural network (GNN) architecture designed to operate on graph-structured data. Introduced by Petar Veličković et al. (Veličković et al., 2018) in 2017 in their paper *"Graph Attention Networks"*, GATs leverage attention mechanisms to dynamically weigh the importance of neighboring nodes when aggregating information. This allows GATs to capture complex relationships and dependencies in graph data more effectively than traditional GNNs. The core of the Graph Attention Networks includes the Graph-structured Data that consists of nodes (entities) and edges (relationships between entities) where each node and edge can have associated features, the Attention Mechanism that computes the importance of neighboring nodes for a given node using self-attention, Graph Attention Layer computes the output features for each node by aggregating from its neighbors, weighted by attention score between node i and node j is computed as Equation(1), and Equation(2) where the attention score is normalized, and the last core, Multi-head Attention to stabilize learning and capture different types of relationships with multi-head attention which are applied in parallel, and the outputs are concatenated or average using Equation(3).

$$e_{ij} = LeakyReLU(a^T[Wh_i || Wh_j]) \tag{1}$$

$$a_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in N(i)} \exp(e_{ik})} \tag{2}$$

$$h'_i = ||_{k=1}^{K} \sigma \left(\sum_{j \in N(i)} \alpha_{ij}^k W^k h_j \right) \tag{3}$$

RESNET

ResNet is a foundational architecture in deep learning, enabling the training of very deep networks and achieving state-of-the-art performance across a wide range of tasks. Its innovative use of residual learning and skip connections has inspired numerous subsequent architectures and remains a cornerstone of modern computer vision.

ResNet (Residual Networks) is a groundbreaking deep learning architecture introduced by Kaiming He et al. in 2015 in their seminal paper, *"Deep Residual Learning for Image Recognition"* (He et al., 2015). ResNet revolutionized the field of computer vision by enabling the training of extremely deep neural networks (with hundreds or even thousands of layers) without suffering from the vanishing gradient problem, which had previously limited the depth of neural networks. The core idea of ResNet is the introduction of residual blocks. Instead of learning mapping directly, Resnet learns the residual mapping. A residual block can be expressed as:

$$y = F\ (x, \{W_i\} + x \tag{4}$$

Where x is the input to the block, $F\ (x, \{W_i\}$ is a residual function to be learned, y is the output of the block, and term x is called skip connection which allows the input to bypass one or more layers.

ResNet has architecture variants that come in various depths, such as ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152, where the number indicates the total number of layers. Deeper variants (e.g., ResNet-101, ResNet-152) use bottleneck layers to reduce computational complexity. A bottleneck layer consists of: A 1x1 convolution to reduce dimensionality, A 3x3 convolution for feature extraction, and A 1x1 convolution to restore dimensionality. The application of RestNet could used for image classification, medical image segmentation tasks, object detection, and so on.

COSINE SIMILARITY

Cosine similarity is a versatile and efficient metric for measuring similarity across various domains. In their book, Theodoridis and Koutroumbas (Theodoridis & Koutroumbas, 2006) define cosine similarity as a measure of similarity between two vectors in an inner product space. The formula for cosine similarity is given in Equation(5) below:

$$Cosine\ Similarity = \frac{A\ .\ B}{||A||\,||B||} \tag{5}$$

$$A.B = \sum_{i=1}^{n} A_i\ .\ B_i \tag{6}$$

$$\|A\| = \sqrt{\sum_{i=1}^{n} A_i^2}, \ \|B\| = \sqrt{\sum_{i=1}^{n} B_i^2} \quad (7)$$

Where A and B are the vectors being compared, A.B is the dot product of vectors, as calculated in Equation (6), $\|A\|\|B\|$ are the Euclidean norm (magnitudes) of vectors, calculated as in Equation (7). It measures the cosine of the angle between two non-zero vectors in an inner product space, providing a value between -1 and 1. A value of 1 indicates perfect similarity, 0 indicates orthogonality (no similarity), and -1 indicates perfect dissimilarity. Cosine similarity is particularly useful for comparing high-dimensional data, such as text or image embeddings, due to its efficiency, scale invariance, and interpretability.

METHODOLOGY RESEARCH

Methodology in research refers to the systematic, theoretical, and structured approach used to conduct a study. As illustrated in Figure 2, the nail disease classification framework using a Graph Attention Network (GAN) and ResNet follows a comprehensive research flow. This flow includes several key stages: Data Collection, Processing & Augmentation, Feature Extraction, Graph Construction, Graph Neural Model Implementation, Training & Optimization, and Evaluation & Metrics. Each stage is designed to ensure the model effectively captures spatial and textural relationships in nail images, optimizes performance, and achieves high diagnostic accuracy.

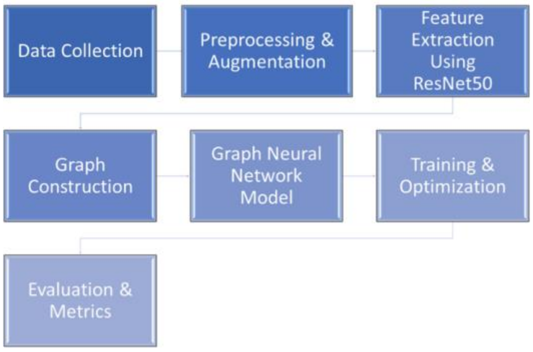

Figure 2. Flowchart Methodology Research

Source: Research Data

The explanation of each stage in methodology research is as follows:

a. Data Collection: Gather nail disease images from Kaggle (Gurav, 2024) and organize images into 6 class nail categories, including blue finger, acral lentiginous melanoma, pitting, onychogryphosis, clubbing, and healthy nails. This image has an RGB in JPEG format with an amount of 3835 images. This dataset split into two, including:
   1) Data Training: has a total of 3744 images where 735 images of acral lentiginous melanoma, 323 images of healthy nails, 677 images of onychogryphosis, 603 images of blue finger, 767 of clubbing, and 639 images of pitting.
   2) Data Testing: has a total of 91 images where 18 images of acral lentiginous melanoma, 20 images of healthy nails, 12 images of onychogryphosis, 9 images of blue finger, 16 images of clubbing, and 16 images of pitting.

b. Preprocessing and Augmentation: To improve model generalization, images undergo:
   1) Resizing to a standard 224×224 resolution.
   2) Normalization using ImageNet statistics with Mean: [0.485, 0.456, 0.406] and Std: [0.229, 0.224, 0.225]
   3) Augmentation Techniques: set property Random horizontal flip, Random rotation (50°), and contrast enhancement.

c. Feature Extraction Using ResNet50: Utilize a pre-trained ResNet50 model (without classification layers) and extract deep feature embeddings from nail images.

d. Graph Construction for GAN: Compute similarity between image features using cosine similarity define adjacency matrix and construct an edge list for graph representation.
e. Graph Neural Network Model: Implement a Graph Attention Network (GAT) or Graph Convolutional Network (GCN) to process extracted features through graph layers.
f. Training and Optimization: set Optimizer: AdamW (learning rate = 0.0005), Loss Function: Negative Log-Likelihood (NLL), and Epochs: 300.
g. Evaluation & Metrics: Model performance is measured using: Accuracy, F1-Score, Precision & Recall, Confusion Matrix, and Visualize classification performance and misclassifications.

RESULTS AND DISCUSSION

The classification performance of nail diseases, as shown in the confusion matrix in Table 1, demonstrates that the model combining Graph Attention Network (GAT) and ResNet achieves an accuracy of 0.8791 (88%). The majority of predictions are correct, indicating strong model performance. A detailed analysis of the results, illustrated in Figure 3, reveals that the diagonal values represent correctly classified instances for each category, while some misclassifications occur, particularly for "Blue Finger" and "Clubbing". Specifically:

a. Acral Lentiginous Melanoma (Melanoma): All 18 samples were correctly classified.
b. Healthy Nail: All 20 samples were correctly classified.
c. Onychogryphosis: All 12 samples were correctly classified with no misclassifications.
d. Blue Finger: Out of 9 samples, 8 were correctly classified, but 1 was misclassified as "Melanoma".
e. Clubbing: Out of 10 samples, 4 were misclassified as "Blue Finger", and 2 were misclassified as "Onychogryphosis".
f. Pitting: Out of 12 samples, 4 were misclassified as "Onychogryphosis".

These results highlight the model's strengths in accurately classifying most nail disease categories while identifying areas for improvement, particularly in distinguishing between visually similar conditions like "Blue Finger" and "Clubbing".

Table 1. Performance of Evaluation Model

Accuracy	F1-Score	Precision	Recall
0.8791	0.8602	0.8801	0.8873

Source: Research Data

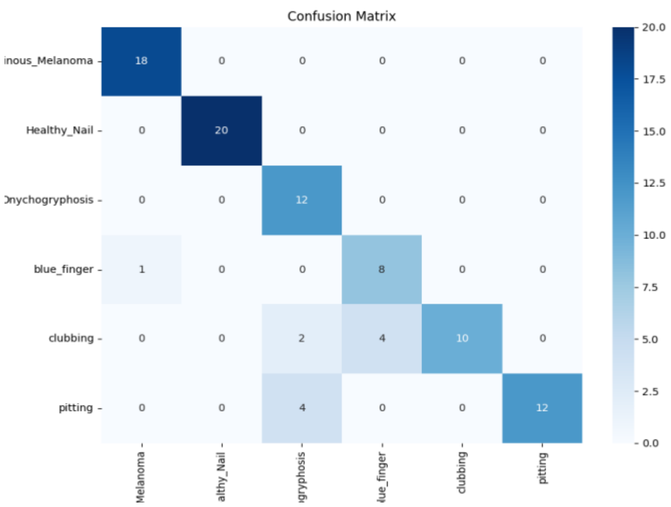

Figure 3. Confusion Matrix of Model
Source: Research Data

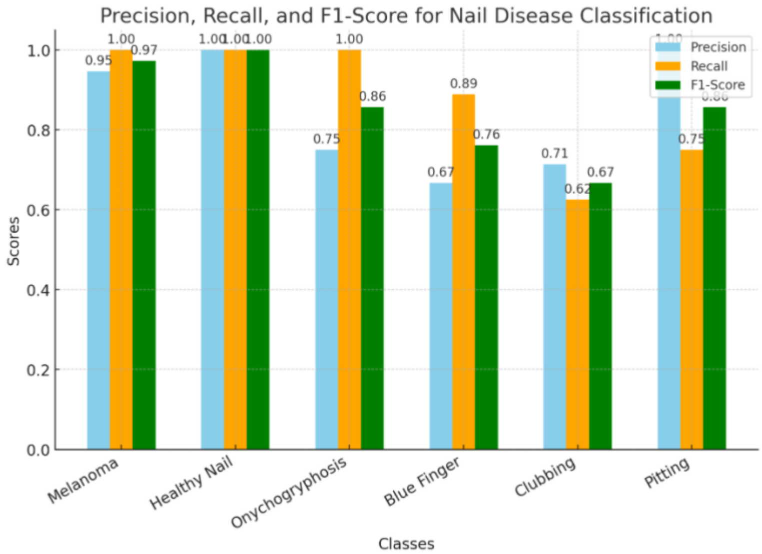

Figure 4. Precision, Recall, and F1 Score in each class of nail disease classification
Source: Research Data

The confusion matrix, along with the Precision, Recall, and F1-Score for each nail disease classification, provides the following insights as illustrated in Figure 4:

a. Melanoma and Healthy Nail achieved the highest classification performance with near-perfect Precision, Recall, and F1 scores (above 0.95). This indicates that the model is highly confident and accurate in identifying these categories.
b. Onychogryphosis showed a lower Precision (0.75) but a perfect Recall (1.00), meaning the model correctly identifies all true cases but has some false positives.
c. Blue Finger had moderate Precision (0.67) and Recall (0.89), suggesting some misclassifications occurred.
d. Clubbing had the lowest Recall (0.625) and F1-Score (0.667), indicating difficulties in correctly identifying all true instances.
e. Pitting achieved perfect Precision (1.00) but slightly lower Recall (0.75), meaning some true cases were missed.

Overall, the classification model performs well, but improvements can be made in distinguishing diseases with lower recall scores. Techniques like additional data augmentation, fine-tuning hyperparameters, or using advanced neural network architectures (e.g., Graph Neural Networks or ResNet variants) may enhance performance further.

CONCLUSION

The analysis of the nail disease classification model using deep learning techniques, specifically ResNet and Graph Neural Networks (GNNs), demonstrates promising results. The model effectively classifies Melanoma and Healthy Nails with high precision, recall, and F1-score, indicating strong predictive accuracy. However, certain categories such as Clubbing, Blue Finger, and Pitting exhibit lower recall and F1 scores, suggesting the need for further optimization.

Misclassifications could be attributed to visual similarities between certain nail diseases, imbalanced datasets, or feature extraction limitations. To improve performance, future research could explore data augmentation, balanced dataset training, hyperparameter tuning, and advanced GNN architectures for enhanced feature representation and classification. Overall, the study confirms the potential of deep learning in medical image analysis for nail disease classification. By refining the model and leveraging larger, more diverse datasets, the accuracy and generalizability of nail disease classification can be significantly improved, aiding early detection and diagnosis in medical practice.

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