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# Chronic Kidney Risk Prediction Through Nail Abnormalities Identification Using AI Image Processing

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## Abstract

Nail alterations have been observed in patients with chronic kidney disease (CKD) due to the buildup of uremic toxins in the blood. Many of these conditions present overlapping visual features, making them difficult to distinguish, especially for non-specialists. Although current research has explored differences between abnormal and healthy nails, classification within a single AI model remains limited. This study aims to develop an artificial intelligence (AI) system capable of classifying some nail conditions associated with CKD, including Lindsay's nails, splinter hemorrhages, onycholysis, leukonychia, and normal nails, using photographic images. A total of 564 publicly available images were validated for labelling accuracy and divided into training, validation, and test sets, with all images categorised into five classes. Model development was conducted using Python on Google Colab with a batch size of 32. Data augmentation techniques, including rotation, zoom, shear, horizontal flipping, and rescaling, were applied to improve model generalisability. Four convolutional neural network (CNN) architectures (VGG16, Xception, ResNet50, and EfficientNet) were trained for 50 epochs. The highest performance was achieved by VGG16, with a test accuracy of 87%, followed by Xception (65%), and both EfficientNet ResNet50 (20%). Confusion matrix analysis further confirmed the strong performance of the VGG16 model. Overall, this study demonstrates a potentially efficient and low-cost solution for assisting early identification of CKD through nail assessment, representing a promising step toward real-world screening applications. Future development should focus on expanding the dataset and improving the model's accuracy.

## Keywords
Chronic Kidney Disease (CKD), Lindsay's Nails, Artificial Intelligence (AI), Convolutional Neural Networks (CNN), and Image Classification

## 1. Introduction
Chronic Kidney Disease (CKD) has become one of the biggest public health issues of the 21st century. As of 2023, nearly 800 million people worldwide are living with CKD, making it the ninth leading cause of death globally (University of Glasgow - University News - Archive of News - 2025 - November - Chronic Kidney Disease Now Affects More than 780 Million People Worldwide 2025). In Thailand, this issue is particularly alarming, with about 17.5% (over 10 million people) of the population affected by CKD (Kanjanabuch and Takkavatakarn 2020). Unfortunately, many people in Thailand do not know they have the disease until it reaches an advanced stage. The

disease often has no symptoms in its early phases. In fact, nearly 1 in 2 people with CKD remain undiagnosed until their condition is serious (Carpio et al. 2021), which makes treatment much harder and more expensive.

The main reason for this delay is that standard blood tests, which measure waste products like creatinine, are not very effective at detecting the disease early. In many instances, a patient might lose up to 50% of their kidney function before a standard blood test shows any abnormal results (Gounden et al. 2024). By the time these chemical levels rise in the blood, kidney damage is often permanent. This highlights the urgent need for easier, quicker, and more accessible ways to screen for the disease before it becomes critical.

One promising solution is studying our nails. The nail bed contains tiny blood vessels and nerves, making it a window to the rest of the body. When the kidneys do not function properly, toxins build up in the blood and often cause visible changes in the nails. Research indicates that over 70% of patients with kidney problems develop nail abnormalities (Niema et al. 2019).

A few of the nail conditions that could be a result from CKD include:

- Lindsay's Nails —also called half-and-half nails—is a nail change that is often seen in people with chronic kidney disease and is thought to result from changes in blood flow, melanin deposition, and nitrogen waste buildup affecting the nail bed. It is most commonly seen in patients with CKD, with around 12% to 41% frequency (Kabra et al. 2022; Riaz et al. 2022). CKD causes uremic vascular bed changes, capillary wall thickening, and dilatation distally. It also correlates with the duration of renal failure/dialysis. This occurs due to uremic vascular changes, and the build-up of nitrogenous waste may change nail color (Saud Mohammed Raja 2021)
- Splinter Hemorrhages—a small, thin, red-to-reddish-brown line of blood that appears under a fingernail or toenail, resembling a splinter. They are caused by trauma to the nail, like stubbing a toe or hitting a finger, or by medical conditions that damage small blood vessels. The prevalence of splinter hemorrhages in CKD patients appears to range from about 4% up to 19% (Kabra et al. 2022; Riaz et al. 2022). Splinter hemorrhages can indicate CKD because CKD causes nail-bed capillaries to be fragile due to uremic microangiopathy and endothelial dysfunction. Platelet dysfunction in uremia can cause easy microbleeding, so secondary infections or minor trauma will be worsened by poor vascular repair. Therefore, the presence of splinter hemorrhages may indicate fragility and an abnormal platelet function, making it an indirect marker for CKD effects. (Niema et al. 2019)
- Normal Nails—a healthy-looking nail that does not require any treatment.
- Onycholysis—the separation of the nail plate from the nail bed, which is typically caused by trauma, infections, medications, or underlying health issues. The frequency of CKD patients diagnosed with onycholysis ranges from 3% up to 17.8% (Kabra et al. 2022; Riaz et al. 2022). This is possibly due to anemia, mineral imbalances, accumulation of uremic toxins, and CKD treatment. Therefore, the presence of onycholysis suggests the effects of CKD on keratin and other tissue abnormalities (Anees et al. 2018).
- Leukonychia—The partial or full discoloration of the nail plate on one or more fingernails or toenails. Common causes include damage to the nail from hitting, biting, or excessive manicures. It is a less common symptom found in patients with CKD (6%) (Kabra et al. 2022). CKD leads to hypoalbuminemia and decreased nail-bed transparency; anemia, and nutrient deficiencies.

These nail conditions do not mean that they are all due to a person having Chronic Kidney Disease. Research has been done in observing the percentages of patients who have CKD, who likely have a specific nail condition mentioned. However, it can be difficult for the general public and even some doctors to differentiate these conditions because they often appear quite similar. While there are Artificial Intelligence (AI) models that can identify general nail conditions, very few focus specifically on the nail changes linked to kidney disease. This study aims to address that gap by developing an AI system that can automatically identify five categories: Lindsay's Nails, Splinter Hemorrhages, Onycholysis, Leukonychia, and Normal Nails. This research plans to evaluate the performance of four different AI architectures—VGG16, Xception, ResNet50, and EfficientNetB0—when classifying nail beds related to potential risks of CKD, to find a low-cost and accurate prototype for checking health. The goal is to provide a simple, non-invasive tool that could potentially help healthcare workers and the public screen for kidney issues earlier, ultimately saving lives and reducing medical costs.

### 1.1 Objectives

- Evaluate the performance of four deep learning architectures—VGG16, Xception, ResNet50, and EfficientNetB0—in classifying nail bed images into five categories
- Determine which deep learning architecture achieves the highest classification performance for automated nail abnormality detection
- Explore whether nail abnormalities can be automatically identified using AI as potential visual indicators associated with Chronic Kidney Disease risk

## 2. Literature Review

Recent advancements in AI deep learning methods have led to the rapid development of identifying and classifying nail disorders from image screening. The comparison of both CNN and Hybrid Capsule CNN models was developed and compared, dedicated to improving the accuracy of classifying nail disorders (Gunjan et al. 2024). A wide collection of data was gathered through public datasets from the online platform 'Kaggle', which includes images of nails in various conditions, including those such as onycholysis, onychomycosis, Lindsay's nails, and Beau's lines (Thomas et al. 2012). These images then underwent careful preparation through augmentation techniques and resizing, crucial components for lowering the risk of overfitting and improving classification accuracy (Gunjan et al. 2024). Studies as such reflect the high performance of AI utilization regarding nail disorder identification, in which reported performance metrics in the studies of Gunjan et al. (2024) and Nijhawan et al. (2017) indicated accuracies of over 80%, respectively. Other studies experimented with various deep CNN architectures, including VGG16, VGG19, and ResNet50 (Gaurav et al. 2024). Results show that the models can diagnose onychomycosis with accuracies of 88.10%, 98.6%, and 95.2%, respectively. Hybrid approaches have also been explored for nail image analysis. One study proposed a fusion model integrating VGG16 and GoogleNet leverage complementary features from both networks, but the model failed to outperform the standalone VGG16 architecture, suggesting that combining architectures does not necessarily guarantee better results (Pathan et al. 2024). Likewise, Sharma et al. (2024) developed a model that combines VGG16 for feature extraction with a Random Forest classifier to categorize the nail images into four classes: kidney disorder, melanoma, anemia, and healthy nails. However, the study focuses on broad disease classification rather than specific nail abnormalities. It is important to note that most studies analyze the correlation to dermatological diagnosis rather than linking findings to chronic kidney disease, highlighting the limited current research in this particular field of study. Additionally, previous studies by Nijhawan et al. (2026) aimed to train two AI models, MobileNetV2 and the Vision Transformer model, to test whether adding synthetic images improved the AI model's ability to identify different nail diseases. Even though deep learning models were proven to be reliable in dermatologist-level accuracy in identifying skin cancer images (Esteva 2017), most research has yet to explore the method of utilizing nail images as risk indicators of diseases like CKD. This is another potential gap that our study aims to navigate.

Chronic kidney disease affects multiorgan systems, therefore symptoms can show up on the skin or nails (Kabra et al. 2022). In a cross-sectional study done on 100 CKD patients, 60% of the patients experienced nail manifestations. Nail abnormalities are more common in patients undergoing hemodialysis compared to healthy individuals (Saray 2004), and are more likely to be present in patients with end-stage renal disease on regular hemodialysis (Galal 2025). The most frequent disorders that showed up were longitudinal ridges (20%), half-and-half nails (12%), leukonychia (6%), pitting nails (6%), onychomycosis (5%), absence of lunula (4%), splinter hemorrhage (4%), and onycholysis (3%) (Kabra et al. 2022). In a different cross-sectional study aiming to determine the frequency of nail disorders in CKD patients undergoing maintenance hemodialysis, researchers found that 197 out of 292 cases (67.5%) exhibited at least one nail disorder. 119 (40.8%) patients had half-and-half nails, 56 (19.2%) patients had splinter hemorrhages, 47 (16.1%) patients had absent lunula, 16 (5.5%) patients had chromonychia, 15 (5.1%) patients had Beau's lines, 19 (6.5%) patients had Melanonychia, and 52 (17.8%) had onycholysis (Riaz et al. 2022). This research also concluded that there is an association between aging and nail disorder and an association between nail disorder and duration of dialysis. Furthermore, Udayakumar et al. (2006) reported that patients undergoing hemodialysis frequently showed nail changes such as half–and-half nails at 21%, being the most prevalent manifestation in the study. Similarly, a study by Chittoory (2020) reported that 52% of the study population, consisting of CKD patients, developed nail changes, including Lindsay's nails (34%), Beau's Lines (15%), and Koilonychia (3%). As the severity of the kidney disease increases, the symptoms become more prevalent in the population, with 68% showing nail changes. These results strengthen the relationship between CKD and nail abnormalities, while highlighting the importance of incorporating dermatological assessments into approaches for predicting systemic diseases, such as CKD. Based on clinical literature, nail abnormalities such as Lindsay's nails, splinter hemorrhages, leukonychia, and onycholysis have been reported in patients with CKD, which motivated their selection as target classes in this study.

While AI-based imaging demonstrates strong potential in classification, the majority of existing studies tend to focus on their connections to dermatological diagnosis rather than systemic diseases such as CKD. Clinical literature reports that nail abnormalities such as Lindsay's Nails may serve as a valuable indicator of renal impairment in patients diagnosed with CKD, especially when serum creatinine is unavailable (Raja 2021). This highlights the potential for AI-image processing to extend beyond the surface-level classification toward a non-invasive risk screening tool for CKD, aiming to identify or determine individuals who may benefit from further medical testing.

## 3. Methods

A Deep Convolutional Neural Network (CNN) based machine learning classification technique has been used, trained, tested, and validated to aid in differentiating between different nail conditions related to chronic kidney disease (CKD) by making use of nail images. Nail images are obtained by accessing publicly available image repositories and open-source datasets. They are considered the inputs to this system, and it outputs the predicted nail bed condition based on the given inputs.

### 3.1 Data Augmentation

Since each picture contains a format and a size that differ from those of other pictures, the augmentation process is conducted with geometric transformations such as rotation, width shifting, horizontal flipping, and shearing. This process produces a slight change in the duplicated images from the original pictures that were input. It is a successful method for producing high-quality and relevant data for training the AI models and reducing potential errors of the classification (Shorten and Khoshgoftaar 2019, as cited in Suha and Sanam 2022).

The simplest and most frequently used traditional geometric data augmentation methods include affine transformations, such as rotation, translation, scaling, shearing, and flipping. Another type of transformation is non-affine geometric transformations that are used to imitate composite images. The typical non-affine methods are projective or perspective transformations, whereby images are produced from many points of view. These are known to be utilized in satellite imaging or UAV surveillance (Mumuni and Mumuni 2022). Some examples of data augmentation techniques of some affine transformations can be seen in Figure 1.

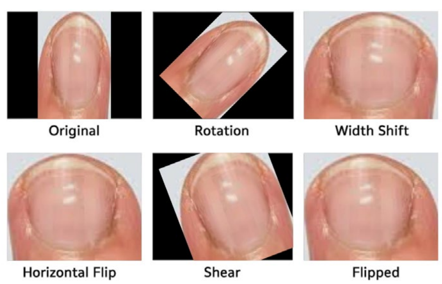


Figure 1. Data augmentation techniques of some affine transformations

Before training, all images were resized to 224 × 224 pixels and normalized to scale pixel values between 0 and 1 to improve model convergence.

### 3.2 Implementation Environment

All of the models were developed using Python 3.12.12 with the TensorFlow 2.19.0 and Keras deep learning libraries. The experiments were carried out on Google Colab, utilizing an NVIDIA T4 GPU with 12.67 GB of RAM. Before training, all images were resized to 224 × 224 pixels to ensure consistency across models. Training was conducted with a batch size of 32 using the Adam optimizer with a learning rate of 0.0001. Categorical cross-entropy was used as the loss function. Each model was trained for up to 50 epochs, with early stopping applied to reduce the risk of overfitting.

### 3.3 Propose CNN Approach

A convolutional neural network (CNN) is one of the most important architectures in deep learning. It is "composed of multiple building blocks, such as convolution layers, pooling layers, and fully connected layers, and is designed to automatically and adaptively learn spatial hierarchies of features through a backpropagation algorithm" (Yamashita et al. 2018). CNN is able to aid in classifying images with its process of training and its convolutional layers (Suha and Sanam 2022).

In this research, the dataset was divided into 73% train, 13% in test, and 13% in validation. The train folder is used for teaching the artificial intelligence (AI) models to classify the images into their respective classes; it is used to provide the model with massive amounts of data to learn patterns, make decisions, and improve its accuracy. The validation folder is a test to observe the model's performance after processing the new information, serving as a simulated exam. Finally, the test category is the final evaluation of the AI's performance, using the results to analyse how well the AI classified its images.

The four pre-trained AI models used in this investigation consist of VGG-16, Xception, ResNet50, and EfficientNetB0.

- VGG16: A type of convolutional neural network model (CNN) that utilizes straightforward stacks of layers for the detection of various image features, including those with complex patterns (Simonyan and Zisserman 2015). VGG-16 serves as a baseline model for image classification due to its strength in feature extraction, acting as a standard for new models.
- Xception: A type of CNN architecture that applies a convolution on each channel and then combines them using a pointwise convolution. Xception is especially helpful for classifying images that are fine-grained and of lower quality (Joshi et al. 2023).
- ResNet50: A residual network with 50 layers designed to reduce the complications of training deeper networks. ResNet50 contains connections that allow the network to skip over layers, preventing vanishing gradients and letting information travel directly across layers (He 2016). This model is widely used for identifying items and image classification.
- EfficientNetB0: A family of CNNs that uses fewer computational resources to achieve high performance. Specifically, EfficientNetB0 uses fewer parameters to extract specific visual characteristics from images. This is done through a method called compound scaling. EfficientNetB0 is especially helpful in its ability to focus on certain stand-out features within images (Tan 2019).

Training and validation accuracy graphs were generated to show the AI model's accuracy for each epoch cycle. The results can be overfitting, whereby training accuracy is very high, but validation accuracy is low, demonstrating that the model memorizes training data but with poor generalization. It can also be underfitting: both training and validation accuracy are low. This indicates that the model fails to learn patterns. An indication of an optimal model will happen when both training and validation accuracy are high and closely aligned, to suggest good generalisation without overfitting.

A confusion matrix was used to evaluate the AI model's prediction skills, and an attention heatmap was utilized to show which parts of the input the model focuses on when making a prediction. The warm colours show how the AI models perceive the regions as important and the cool colours as irrelevant in classifying each image. For statistical analysis to compare model performance, key classification metrics (Accuracy, precision, recall, and F1 score) were calculated for each architecture. Cross-validation results were analysed to ensure robustness of the findings. They are calculated from True Positives (TP) which is when both the actual result and prediction are positive, True Negatives (TN) is when both the prediction is and the actual result is negative, False Positives (FP) is when the prediction is positive but the actual result is negative, and False Negatives (FN), when the prediction is negative but the actual result is positive, aid in evaluating each classification model via their formulas.

Figure 2. shows an example of results from the Grad-CAM (Gradient-weighted Class Activation Mapping) for images of nails with leukonychia, with the model detecting one accurately, and the other one inaccurately, indicating its performance.

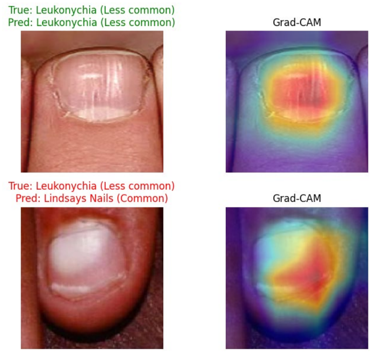


Figure 2. Attention heatmap Grad-CAM results for some of the images

## 4. Data Collection

Data acquisition was used to collect data. There are a total of 564 images of nail beds, some cropped from a publicly available site known as 'Kaggle' (Gurav 2024; Rasanjana 2023; Agrawal 2023; Mittal 2025). Additional images were obtained from publicly available online image sources for research purposes. All of the pictures from the Kaggle links and from Google are color pictures, cropped to focus on one single nail bed for emphasis. In addition to that, the images are taken under good lighting conditions. According to their category, the pictures are labeled as either Lindsay's nails (Common), splinter hemorrhages (Less common), onycholysis (Common), leukonychia (Less common), or normal nails, according to how they were labeled in Kaggle folders, and under the examination of the authors of this study. After the images have been categorized, the dataset contains a total of 105 images of Leukonychia, 111 images of Lindsay's nails, 131 images of normal nails, 110 images of onycholysis, and 107 images of splinter hemorrhages.

## 5. Results and Discussion

### 5.1 Numerical Results

The performance of the four Convolutional Neural Network (CNN) architectures: VGG16, Xception, ResNet50, and EfficientNetB0 was evaluated using standard statistical metrics. These include Precision (exactness), Recall (completeness), F1-Score (the balance between precision and recall), and overall Accuracy.

The results in Table 1 demonstrate a significant variance in how different architectures handled the classification of nail conditions. As shown in the classification reports, VGG16 emerged as the superior model for this specific dataset.

Table 1. Key Classification Metrics for all AI Models Used.

| Model | Accuracy | Precision | Recall | f1-score |
|---|---|---|---|---|
| VGG16 | 87% | 0.8752 | 0.8675 | 0.8677 |
| Xception | 65% | 0.7067 | *0.6533* | 0.6543 |
| Resnet50 | 30% | 0.1657 | 0.3167 | *0.1957* |
| EfficientNet | 20% | 0.040 | 0.2000 | 0.0667 |

The classification reports provided a more detailed look at how each model performed across individual categories:

- VGG16 (Top accuracy): This model showed the best results. It achieved a perfect 1.00 F1-score for Normal Nails (Figure 3), ensuring that healthy individuals are not misdiagnosed. For Lindsay's Nails, a key indicator of CKD, it maintained a high recall of 0.94, successfully identifying the majority of cases.
- Xception (Moderate accuracy): Xception struggled with its diagnosis. While it was fairly good at identifying Onycholysis (0.87 recall), its precision for Lindsay's Nails was lower (0.58) (Figure 4), meaning it often confused other conditions for Lindsay's nails.

- ResNet50 (Low accuracy): The results for ResNet were poor, with an overall accuracy of only 30%. The model failed completely to identify Leukonychia, Normal Nails, and Onycholysis returned scores of 0.00 for these categories. It only showed a high recall for Splinter Hemorrhages (0.92), but with very low precision (0.20), indicating it was likely guessing this category too frequently.
- EfficientNet (Lowest accuracy): This model achieved only 20% accuracy. It predicted Normal Nails for every single image in the test set, failing to recognize any actual disease markers (Figure 5). conclusions. References must be avoided. Also, non-standard or uncommon abbreviations should be avoided, but if essential, they must be defined at their first mention in the abstract itself.

Figures 3, 4, and 5 display the confusion matrices of the models.

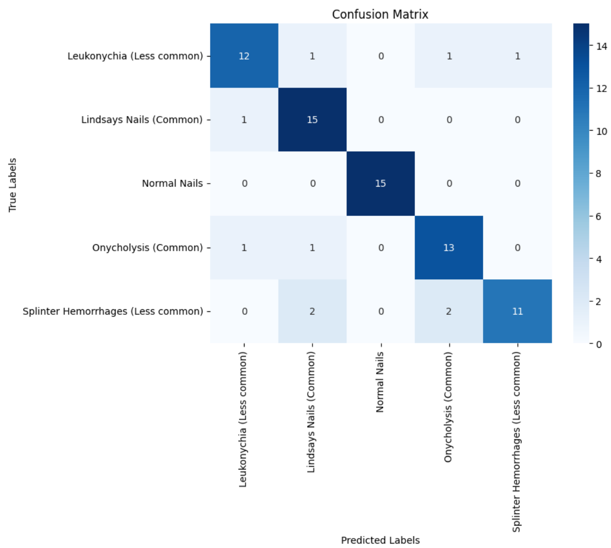


Figure 3. Confusion matrix of VGG16

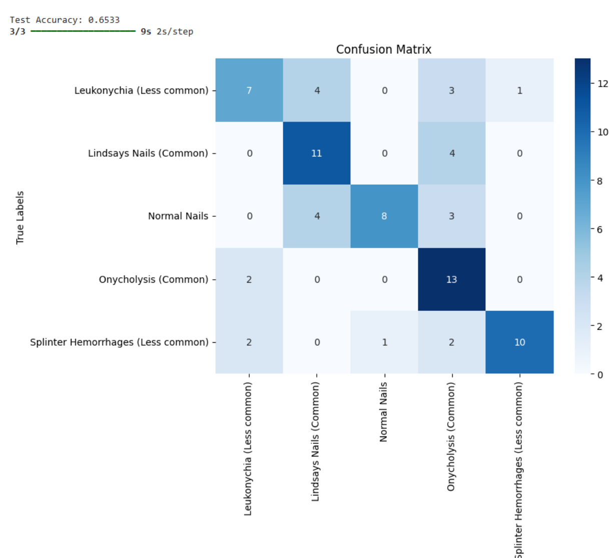


Figure 4. Confusion matrix of Xception

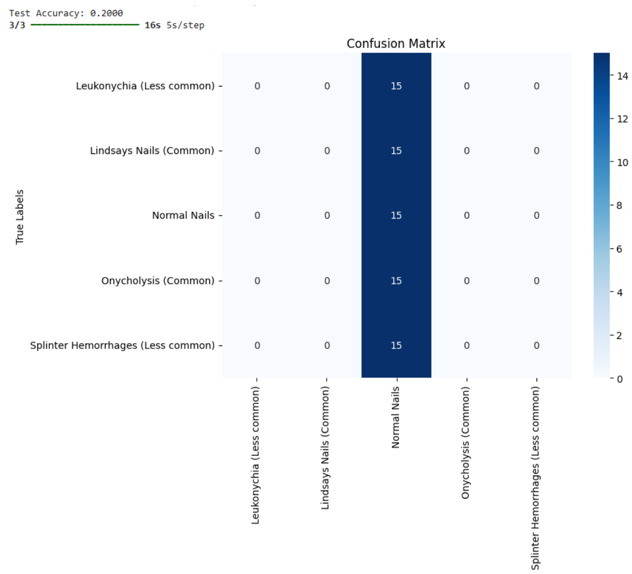


Figure 5. Confusion matrix of EfficientNet

The high performance of VGG16 (87%) compared to the much lower scores of ResNet (30%) and EfficientNet (20%) is a significant finding. In deep learning, more complex models like ResNet and EfficientNet often require much larger datasets to learn effectively. Given that this study used a focused dataset of 564 images, the simpler and more robust architecture of VGG16 was better suited for the task.

The confusion matrices suggest that the models most frequently struggle with Leukonychia and Lindsay's Nails. This is scientifically understandable, as both conditions involve a whitening of the nail plate, making them visually similar to an AI that is still learning subtle texture differences.

## 5.2 Graphical Results

The graphical comparison of model performance is illustrated in Figure 6 and Figure 7. The bar charts show the differences in accuracy, precision, recall, and F1-score among the four CNN architectures. VGG16 demonstrates the highest performance across all evaluation metrics compared to Xception, ResNet50, and EfficientNetB0. The graph also demonstrates that the performance differences between the models are small for some metrics, indicating that all architectures were capable of learning relevant nail features, although VGG16 achieved the most consistent results. The recall being high and precision being low from the results of ResNet50 and EfficientNetB0 successfully identify most positive cases, but incorrectly classify a higher number of negative samples as positive.

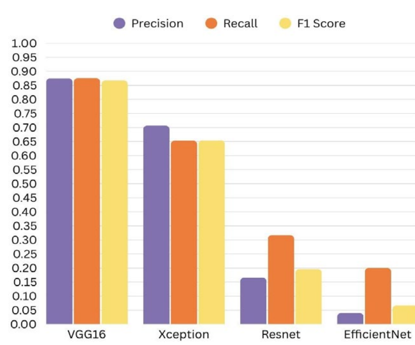


Figure 6. Bar chart of precision, recall, and F1 scores for all four models

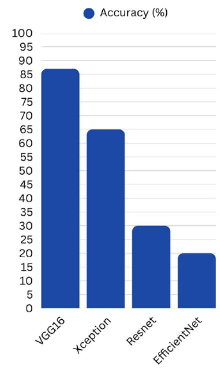


Figure 7. Bar chart of the accuracy results for all four models

### 5.3 Proposed Improvements

Increasing the dataset will train the models to be more familiar with the appearance of nail beds for each condition, potentially resulting in improved accuracy. The investigation could increase in reliability if communication with medical professionals and dermatologists to accurately categorise the images to its classes were possible. Exploring the precision and accuracy with other CNN architectures, such as ConvNeXt or DenseNext, could lead to better analysis of the best model performance.

Future studies may involve developing an AI multi-model where nail classification is linked with various other non-invasive data sources, such as the medical history of patients and other demographics. For instance, further incorporation of medical records paired with convolutional neural network models may improve accuracy and reduce any false positives that are often found among nail abnormalities that may appear visually similar. Additionally, more intricate networks could be explored to improve the model's ability to detect nuances of textures and colors.

### 5.4 Validation

To ensure objective model evaluation, the 564 nail image dataset was split into training, validation, and testing sets. The CNN architectures were trained using the training set, and overfitting was avoided; model performance was tracked using the validation set. The final assessment of the model's performance was conducted using the testing set. To ensure a fair comparison of model performance, all four CNN architectures were trained using the same dataset, preprocessing procedures, number of epochs, and evaluation metrics. Performance metrics such as accuracy, precision, recall, and F1-score were compared across all models in order to verify the findings. The consistent improvement in performance observed in the VGG16 architecture suggests that the model provides more stable feature extraction for nail image classification compared to the other tested architectures.

### 5.5 Prototype Graphical User Interface (GUI) Implementation

After the evaluation of each AI model, we decided to use the accuracy of VGG16 to help in detecting nail conditions using a graphical user interface (GUI). Users can take a photo of their nails or upload a picture to find out if their nail is normal or not. The website will output the nail condition, as well as the description of the output in the comments. This can be referred to in Figure 8.

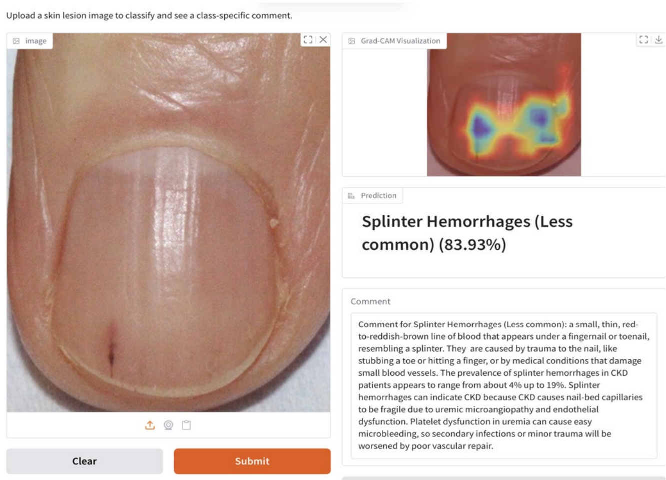


Figure 8. Appearance of the graphical user interface

## 6. Conclusion

This study demonstrates the use of Artificial Intelligence as a non-invasive and accessible approach in analyzing images that may be associated with the risk of Chronic Kidney Disease. By training and evaluating 4 different CNN architectures—VGG16, Xception, ResNet50, and EfficientNetB0—on a dataset of 564 images, the results show that VGG16 significantly outperformed the other architectures, with an accuracy of 87% and an F1 score of 0.8677. These findings help address the research objectives by evaluating the performance of multiple deep learning architectures and identifying which model has the best classification ability based on performance.

The confusion matrices of all models also highlight the challenges of distinguishing visually similar nail disorders, specifically leukonychia and Lindsay's nails, indicating the need for further training, larger datasets, and more advanced CNN architectures. Overall, this study's findings contribute to the use of AI-assisted tools in medical screening by demonstrating the feasibility of automated nail abnormality classification. It could serve as a supportive tool in analysing nail images for early risk screening of CKD, while showing that further clinical validation is required.

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## Biographies

**Nunnaphat Wongsuwan** is a grade 11 student at Anglo Singapore International School, with a strong interest in medicine, artificial intelligence, and research. As the Communications and Outreach Officer of a nonprofit organization, Restoring Rainbows Bangkok, Nunnaphat has helped coordinate initiatives to donate stationery supplies to many foundations across Bangkok. Besides maintaining a 3.95 GPA, Nunnaphat is actively involved in the school's badminton team, robotics club, math and science competitions, and volunteer initiatives with local charitable organizations. Nunnaphat plans to pursue a six-year medical degree in the future.

**Piratchaya Tanjapatkul** is a grade 11 student at the International Community School (ICS) with a passion for sciences and navigating the medical field. With a curiosity for artificial intelligence, Piratchaya enjoys exploring how different forms of technology can be incorporated into the current healthcare systems in order to improve patient care. As part of her school project, Piratchaya is currently investigating suitable physical therapies that will improve muscle movement for the elderly. Since CKD is a prevalent issue among the elderly, Piratchaya has particularly been focusing on ways to improve the quality of life for older adults.

**Nattanan Singhapanich** is a grade 11 student at the International Community School (ICS) with a profound interest in the medical sciences and community health. Nattanan has spent significant time volunteering and shadowing in diverse clinical settings across Thailand, gaining insight into healthcare delivery in both urban and rural environments. As part of a recent Capstone project, Nattanan collaborated with a local foundation for children with disabilities to implement a curriculum on herbal hygiene products. Currently engaged in developing AI-based medical innovations, Nattanan plans to pursue a career in medicine further to explore the intersection of healthcare and assistive technology.

**Natwasa Singhapanich** is a grade 10 student at International Community School Bangkok with a strong interest in how innovation and artificial intelligence can be applied to improve healthcare. At school, Natwasa is a member of the Biochemistry Research Club and the Khun Mhor Medical Club, where she explores topics related to medical science. Having trained in ballet for 13 years and competing in her school's varsity basketball team, Natwasa developed a strong appreciation for the science of the human body, including injury prevention, recovery, and physical performance. Her latest ongoing research project is a smart knee brace aiming to alleviate pain for osteoarthritis patients or patients who suffer from knee pain, such as athletes.