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Enhanced Forearm Vein Detection Using a U-Net Model Integrated with ResNet for Superior Accuracy

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Abstract

The discovery of veins in the forearm continues to be a significant obstacle, especially in susceptible patient groups such as the elderly, youngsters, and those who are obese. Conventional approaches typically fail to find veins effectively on the very first try. Not only does this make the patient uncomfortable, but it also reduces the effectiveness of the therapeutic procedure. To solve this ongoing problem, we suggest a cutting-edge method that uses a U-Net model coupled with ResNet (Residual Network). This technique is intended to considerably improve the accuracy of vein recognition. Because of the addition of ResNet, the model's capability to learn detailed elements in medical pictures is much enhanced, which results in a significant improvement in its performance. The performance of the proposed method achieved 96% accuracy when applied to a dataset of forearm medical photos, an 80% precision rate, and a minimum loss function of 0.06. These results were achieved through the application of the Enhanced Forearm Vein Detection method. By demonstrating that the model can outperform conventional approaches, these findings indicate that the model represents a significant advancement in the field of medical picture segmentation and vein recognition. The use of this cutting-edge method provides medical practitioners with a revolutionary instrument that guarantees a venous access procedure that is quick, accurate, and less invasive.

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Keywords: Advanced Forearm Vein Detection, U-Net Architecture, ResNet Integration, Convolutional Neural Networks (CNN), Medical Image Segmentation.

1. Introduction

Intravenous (IV) fluids form a key part of current medical practice, supporting a range of diagnostic, therapeutic, and laboratory interventions including blood taking, administration of drugs, blood transfusion, and parenteral nutrition. Despite this, successful venous access can cause considerable difficulty. As access via an IV is important and must ideally be consistently reliable, a demand for effective, efficient, and reliable alternatives is imperative.

A variety of techniques have been developed to counteract such obstacles, including the use of ultrasound technology, infrared vein finder, multispectral imaging, and robotic-guided interventions. Nevertheless, each of these techniques comes with its inbuilt practicality: success at first try is not guaranteed, supporting technology can have a high price tag, and professionals must receive specific training in utilizing these techniques effectively. In addition, individual patient factors such as body shape and dimensions and, in part, the subjective basis for certain techniques, reduce overall dependability [2][3]. Consequently, even with technological development, forearm vein detection continues to cause difficulty, and therefore, a more durable alternative is warranted.

The most recently developed artificial intelligence, specifically deep learning, techniques have shown considerable potential for analysis of medical images. Convolutional Neural Networks (CNNs) have outperformed traditional image processing algorithms in a range of medical processes including tumor analysis, organ segmentation, and mapping of blood vessels, through an ability to learn complex, hierarchical structures [4]. In this work, an augmented deep learning technique for forearm vein detection is proposed and utilizes U-Net, a proven algorithm for segmentation, and incorporates it with Residual Networks (ResNet) in a model designed to both accurately and efficiently segment forearm, subcutaneous veins.

2. Related Work

Throughout the years, numerous techniques have been proposed for improving the sensitivity, specificity, and overall performance of vein detection algorithms. Despite having potential, such techniques face obstacles that necessitate the use of more complex techniques—like deep learning—to address the inherent complications. One such significant technique was proposed in [11] by Francis et al., in which they utilized Contrast Limited Adaptive Histogram Equalization (CLAHE) with Gabor filtering. It started with filtering out the noise in the input images using a combination of median and Gaussian filtering techniques. Thereafter, two instances of CLAHE were performed to enhance contrast and make the veins apparent. Next, Gabor filtering was utilized to amplify vascular structures even more. In conclusion, a region of interest with a clearly defined boundary was segmented using Otsu's thresholding, with intensity being considered for segmentation.

Shah et al. [12] explored Generative Adversarial Networks (GANs), specifically the Pix2pix GAN model, to detect forearm veins. Pix2pix is a conditional GAN wherein generated images depend on input images. The model includes a generator, which learns via inverse loss and L1 loss (computed between the generated and target images), and a discriminator, which uses a PatchGAN approach to differentiate real images from generated ones. This strategy demonstrated high accuracy (0.971) and a Dice coefficient of 0.962, suggesting that GANs can perform effectively even with limited training data—an advantage often critical in medical applications.

In another study, Zhang et al. [13] introduced the Adaptive Gabor Convolutional Neural Network (AGCNN), which combines Gabor filters with CNNs. By replacing standard convolutional layers with Gabor-based layers, the model more effectively captured vein textures. Although the AGCNN achieved slightly lower accuracy (90.87% on the test set) compared to a standard CNN (91.53% on the test set), it required fewer parameters, implying reduced computational demands and potential for faster inference.

Tang et al. [14] took a multimodal approach by extracting five distinct features—speeded-up robust features (SURF), local line structures (LS), global graph representations (GG), forearm width (FW), and forearm boundaries (FB)—from near-infrared (NIR) images. These features were fused at the score level using an entropy-based fusion rule to enhance vein detection accuracy. While this approach achieved strong performance, its complexity may limit widespread clinical implementation, suggesting a need for further research to streamline feature integration.

Focusing on network design, Jing et al. [15] proposed a lightweight U-Net model for subcutaneous vein detection. They made three key modifications to the original U-Net: (1) replacing UpSampling layers with Conv2DTranspose layers to refine vein patterns, (2) applying data augmentation to increase training samples and mitigate overfitting, and (3) adjusting the learning rate and number of epochs to optimize performance. These enhancements improved the Dice coefficient from 0.6239 to 0.7032 and yielded an average accuracy of 88%. Owing to its relatively small size, the lightweight U-Net can be deployed in real-time medical imaging scenarios where computational efficiency is essential.

Despite these advances, the task of accurately detecting forearm veins remains an ongoing challenge in medical imaging. Hence, developing a model that integrates powerful segmentation architectures (like U-Net) with deep residual structures (like ResNet) can provide a robust framework for high-accuracy, real-time vein detection.

3. Material and Method

3.1 Dataset Details and Data Splitting Strategy

To facilitate transparency and reproductivity, in this work, a thorough documentation of the dataset and preprocessing techniques adopted is presented. In terms of datasets, 200 forearm vein images, acquired from Kaggle (kaggle datasets download -d chrismnugent/forearm-veins-nir), with a respective mask for effective supervision during training, form part of the dataset. All preprocessing techniques and datasets were handled with care and partitioned into three respective subsets: a training subset (70%) with 140 samples, a validation subset (20%) with 40 samples, and a testing subset (10%) with 20 samples. For training, a training subset, comprising 140 samples, was adopted for training; during training, complex feature extraction of structures of the veins and hyperparameter search and overfitting countermeasures took place; in parallel, a testing subset, with 20 samples, was adopted for testing and confirming that proposed techniques generalize well over a variety of forearm vein images.

To boost model generalizability and robustness, several techniques for data augmentation were adopted. Horizontal and vertical flipping techniques have been adopted to introduce orientation variation, representing real-life scenarios. In addition, random 180-degree rotation techniques have been adopted to cover a variety of postures in terms of an arm, enhancing model adaptability. In addition, translation and zooming operations have been adopted to introduce variation in terms of positioning and scales, allowing for model generalizability over a variety of distributions in terms of images. Adjustments in contrast have been adopted to cover discrepancies in terms of skin colors and lighting, culminating in an improvement in model performance over heterogeneous groups of subjects. Overall, these preprocessing techniques have played a significant role in enhancing model performance, culminating in a reliable and efficient forearm vein segmentation system.For better compatibility with the deep learning model some data preprocessing techniques were used on the dataset for better training and better performance as demonstrated in Figure 1 .

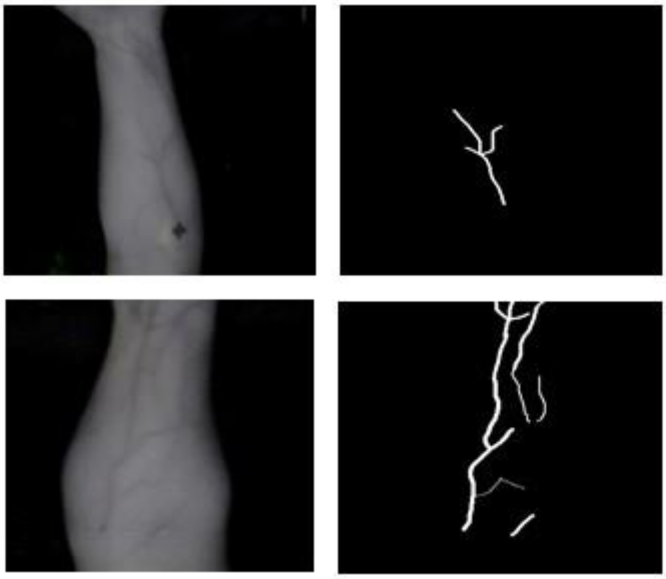

Figure 1:show the Image before processing

3.2 PROPOSED SYSTEM

The proposed method is illustrated in Figure 1. It is applied to forearm images to identify subcutaneous veins.

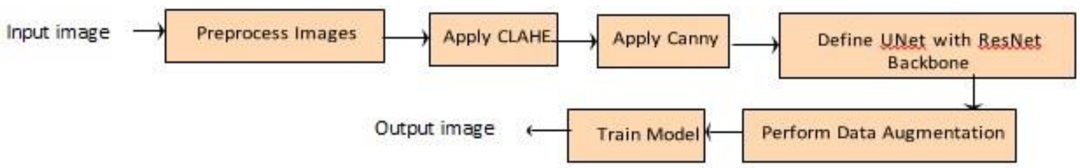

Figure 2: show the proposed method

3.2.1 Preprocessing

To ensure consistency and compatibility with the model's input dimensions, each image was first resized to 256×256256×256 pixels. Next, all pixel values were normalized to the [0,1][0,1] range by dividing by 255.0. This step not only standardizes the input values—preventing excessively large updates during training—but also helps reduce computational costs and improves overall training performance.

Since the model requires three input channels (RGB), the grayscale images were converted to an RGB-like format. This was achieved by replicating the single grayscale channel into three identical channels (Red, Green, and Blue). Practically, a lambda function was used to add the extra dimensions so that the network would interpret the images as if they were native RGB.

To further enhance the visibility of the veins, Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied. CLAHE improves local contrast and reveals finer structural details within the images, making vein patterns more distinct. Additionally, the Canny edge detection algorithm was used to emphasize vein boundaries, aiding the model in distinguishing veins from surrounding tissues.

These preprocessing steps—resizing, normalization, channel replication, contrast enhancement, and edge detection—are critical for maximizing segmentation and detection accuracy, as illustrated in Figure 3.

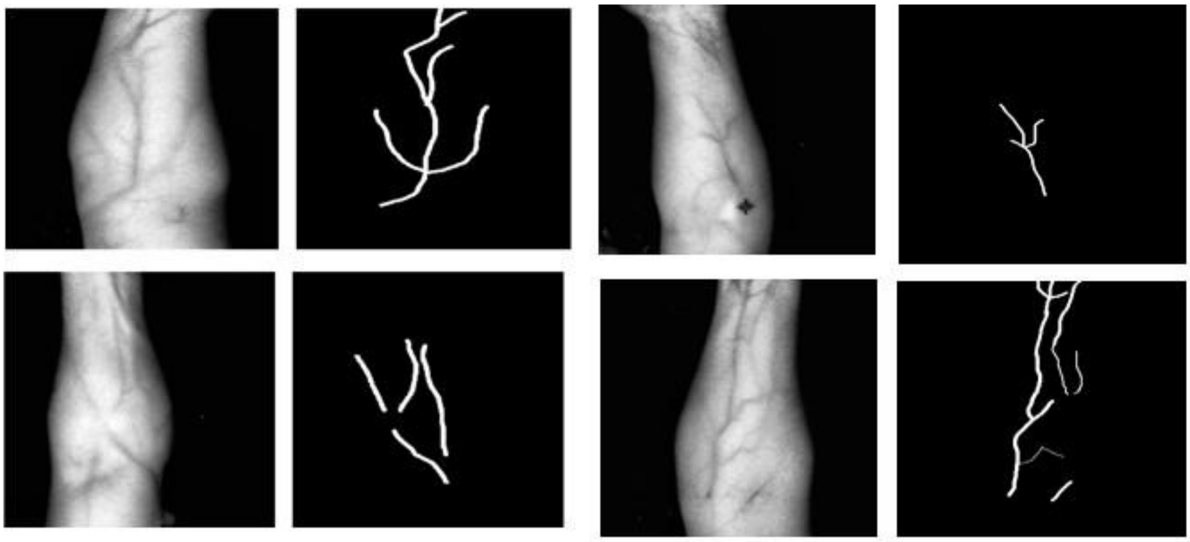

Figure 3- Image after applying CLAHE and Canny

3.2.2 UNet Model with ResNet Enhancement

UNet deep learning network is one of the most employed encoder-decoder based structures, well-known at the present time for its applicability in many medibaal image segmentation problems [6]. Although, the original UNet shows the effective results it may provide the substandard performance in relation to the other more superior DL model [7][8]. In order to overcome these drawbacks and improve the segmentation accuracy, we introduce a new version of UNet which includes ResNet into its structure making it effective for the segmentation of forearm veins.The improved UNet model structure introduced the ResNet layers to the model, which increases capability of detail in the image recognition greatly. The model starts with the encoder inclusion that encompasses two Conv2D layers with filters of dimension (3, 3); the layers are ReLU activated with 'same' padding. The odd layers are then regularized using L2 regularization in order to reduce the complexity of the model while Batch Normalization is applied to make the outputs of layers have zero mean and unit variance. Similarly, MaxPooling2D is applied to down sample and the spatial size The model uses 3 Dropout layers to counter act over fitting during the training phase,In the decoder path, the filters used in the layers are Conv2DTranspose with (2, 2) size and padding = 'same'. These layers are connected with the encoder's outputs by means of concatenation which in term makes usage of feature maps from the

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earlier extracting blocks possible. Addition of the further convolutional layers (Conv2D) and BatchNormalization are introduced to increase accuracy and enhance the stability of the training process.In order to improve the efficiency of the proposed UNet, we incorporate element of ResNet into the network architecture. For prior, ResNet50 which is famous for 50 layers of deep structure [5] comes as a backbone. However, in this work, we adopted only four layers from ResNet, specifically the convolutional layer and its corresponding block output (conv{i}_block3_out) to enhance the model performance while keep the computation cost low. These layers help to store important image details while segmenting and the outputs from these layers are passed through Conv2D with (1, 1) kernel to transform the output to a feature map required by UNet. This transition resizes the dimensions of the outputs appropriately in order to be easily integrated into the final UNet structure.This enhanced UNet model, augmented by ResNet, offers significant improvements in the segmentation of medical images, delivering more precise and accurate results, as illustrated in Figure 2.

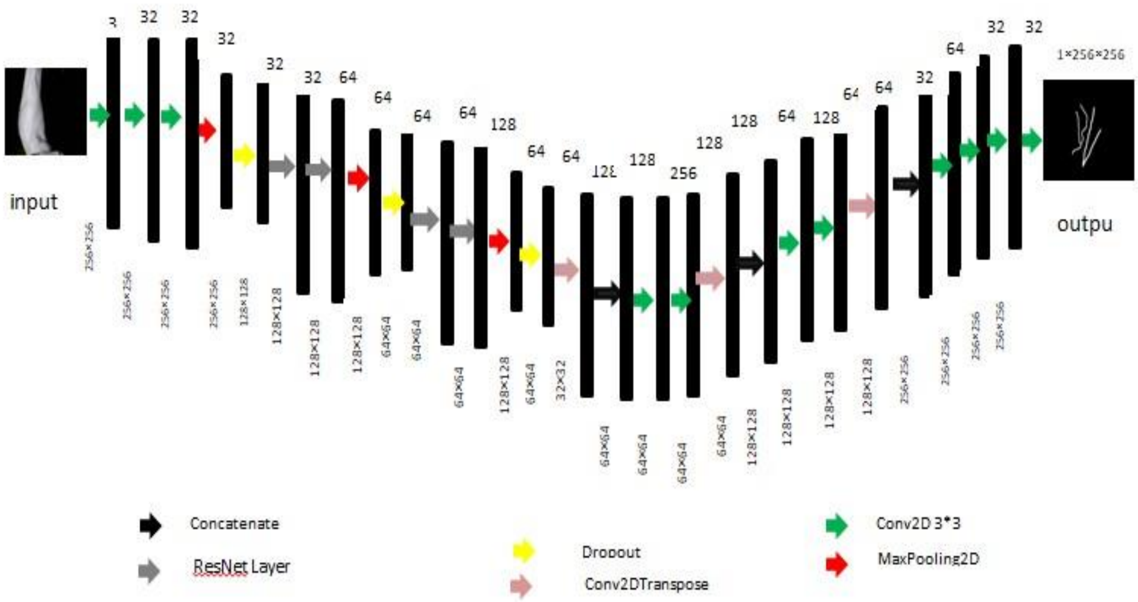

Figure 4: Unet_model_with_Resnet model structure

3.2.3 Data Augmentation Strategy

To make the training more reliable and the model less overfitting during training, we used data augmentation methods by using the ImageDataGenerator from the Keras Library. This procedure randomly transforms the training data which results in variation in the training data and also reduces over fitting. This is because when the images and the corresponding masks are increased in the same proportion, the model is presented with a wider range of training samples thereby improving its performance especially on test datasets. In this research implemented two distinct data generators: One is used for input image and the other one are used for the masks. This approach helps in maintaining the coordination relation between images and their masks as it guarantees the application of the same augmentation to images and their masks when employed for segmentation. This is particularly relevant in the medical imaging domain where the alignment, in the pixel level of the images and the masks is crucial.The augmentation process brings a number of changes that mimic fluctuations in the data set encountered in practice. For example, flipping, shifting, rotating, shearing, and zooming the images means that the orientation, as well as the scale of the images differentiate them and, therefore, create an even bigger variety of training samples. Such transformations give the model a chance for improving the learning of better general features which in turn helps the model in deriving better features for data that it has never seen before.In order to incorporate the augmented images and masks into the data pipeline, a function was designed as follows: generator_with_augmentation This function combines both generators in as far as the images and masks are transformed in the same way at the same time. The end-product is therefore a data generator that is filled with new data and can supplement the already existing aggregation-trained data to the network, in one continuous pass.Below are the specific augmentation parameters utilized in the data generators, as summarized in Table 1.

Table 1: Show the Data Generator Parameters

Parameter	Value
Horizontal Flip	True

Vertical Flip	True
Rotation Range	180
Width Shift Range	0.2
Height Shift Range	0.2
Shear Range	0.3
Zoom Range	0.3
Fill Mode	Constant
Batch Size	4

Therefore, the proposed model augments the data, making the model adapt to a variety of real-world scenarios, thus improving the segmentation outcomes in the test phase. It also aids in avoiding overfitting of the model for the combinations or patterns in the training dataset, thus enhancing the model’s capacity to generalize over different datasets.

3.2.4 Fine-Tuning Strategy for Enhanced Image Segmentation

This is the final tuning of the model and is a very important process of achieving the best performance of the unet_model_with_resnet in the case of segmenting a patient’s image in order to identify blood vessels.This entails manipulating and optimizing different model attributes in order to maximize the perfect score of the set, at the same time preventing overtrain. This process enables one to have better control over how the model learns from the data thus enhancing both generalization ability of the model and on the segmentation results.Since the success of image segmentation depends on the possible features the model picks, the fine-tuning is an important stage in adaptation of the model to the characteristics of the dataset. Parameters adjusted and possibly changed during this process include input shape, number filters, model depth and/or number of layers, dropout rate and/or L2 norm, optimizer, loss function and/or evaluation metric and all of them directly influence the ability of the model to delineate blood vessels and other fine structures.

Key Fine-Tuning Parameters

To improve the segmentation efficiency of the unet_model_with_resnet the following hyper parameters was tuned. They are given below in Table 2:

1. Input Shape: The input shape means the specified size of the images to be received in the model. For this task, the tuple that describes the input shape of the images has been set to (256, 256, 1) and this simply means that the images used herein are of dimensions 256 pixels by 256 pixels and are of grayscale format. This input shape ensures that computations are not time intensive and, at the same time, the resolution needed to capture the small details such as the blood vessels.

2. Number of Filters: That means the number of filters would tell the number of feature maps the model will learn at each of these layers. In all the convolutional layers, we used 32 filters, which we see as an optimal number for both precision and computational requirements.

3. Model Depth: The depth parameter determines the number of layers involved in downsampling and upsampling of the networks in UNet architecture. A depth of 3 was determined which means that the model has three downsampling and three upsampling blocks respectively. This depth is enough to extract hierarchical features without bring more complexity that over fit the model.

4. Dropout Rate: Dropout is coping mechanism in which some neurons are artificially dropped out or removed while the model is being trained so as to reduce overfitting. 0.3 was decided on the basis of which 30% neurons are omitted during each training session to avoid development of over reliance on particular features by the trained model.

5. L2 Regularization: L2 regularization also aims at reducing large weights of the model and thus promotes simpler models that are usually more general. As a result,

we fixed L2 regularization on the convolutional layers at 1e-4. This sort of small regularization factor assists in reduction of overfitting by discouraging complex models while not complicating the learning process.

6. Optimizer: Basically, the use of optimizer plays a fundamental role in determining how the model adjusts its weight during training. We used the Adam optimizer which regulates the learning rate according to the gradients' size while providing a good balance between fast convergence and accuracy. The proposed Adam algorithm is very efficient in handling the problems of loss and the enhancement of models in deep learning tasks.

7. Loss Function: In order to address the sparsity of samples and the imbalance problem which is common in medical image segmentation, a new loss function named weighted_binary_crossentropy was adopted. The weights [1. 0, 1. 0] were used to make both the pixel belonging to the foreground (blood vessels) and the background show equal importance in training the model hence show equal class importance.

8. Evaluation Metrics: To assess the performance of the proposed model, two factors were measured including accuracy and dice coefficient. Accuracy gives the performance measure in terms of the percentage of data which has been classified correctly while Dice gives a measure of the overlap of the segments obtained using the model and the ground truth. Dice coefficient is very useful when used in small and less bulky structures such as blood vessels.

9. Steps per Epoch: Epochs are the quantity of steps that define the number of batches of data which the model goes through in one training cycle. This was set to len(train_images) // 2, thus improving the training time and depending on the amount of data provided and the timeframe to get meaningful changes on the model weights.

10. Pre-trained Weights: To improve the speed of your training and to utilize weights which the program learned in previous epochs, pre-trained weights were used in the ResNet backbone of the used UNet Model. These weights which is referred to as weights_path help the network to have a reference point from which it will improve from in its training so as to aid the blood vessel segmentation task.

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Table 2: Fine-Tuning Parameters for UNet Model with ResNet

Parameter	Value
Input Shape	(256, 256, 1)
Number of Filters	32
Model Depth	3
Dropout Rate	0.3
L2 Regularization	1e-4
Optimizer	Adam
Loss Function	Weighted Binary Crossentropy
Evaluation Metrics	Accuracy, Dice Coefficient
Steps per Epoch	len(train_images) // 2
Pre-trained Weights	weights_path

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Vol.20 No.1 Mar 2025

4.Result

4.1 Model Training

In this study , we trained an improved model for medical image segmentation, the UNet model improved with ResNet because of its versatility in the field of medicine. Previous studies[16], [17], [18] have shown that this integrated model has been very effective in the medical field for segmentation of various ailments such as thyroid nodules, chest X-Ray and brain tumours. Because of its effectiveness in these areas, the proposed the use of this improved UNet model in detecting and segmenting forearm veins, this is a complex venture given the fine detail that is comprised of veins in the forearm.

4.1.1 Training Process

The dataset that will be used in training the model has been trained specifically for forearm vein detection while some experiments were conducted to determine the best parameters for training the model. But, one of the best features tweaked during the training was the learning rate which determines the rates of convergence to the correct solutions. Several learning rates were tried with the learning rate starting with a higher value of 0. 1 and which reduces gradually to low numbers such as 0. 0001. But these issues were initially not very efficient because increasing the learning rate resulted in severe problems with detecting forearm veins at all. In particular, the model often deleted parts of the vein structures and failed to distinguish between the skin tissue and veins, or exhibit a poor level of segmentation.Finally, after various attempts at adjusting the various learning rates we decided that the optimum learning rate was 0.2 Based on the results, the respondents could be divided into three groups based on the level of distraction and the first group was clearly the least distracted while the last group was the most distracted hence the 0.2 was the best in between. This learning rate made it possible for the model to pick details of the forearm veins down to the last feature without omitting any essential aspect. It also effectively differentiated between the more various types of tissue to include; veins as well as skin. This was necessary in order to enhance segmentation effectiveness and make sure the model is capable of adapting well to new data sets.

4.1.2 Number of Epochs

Through iterative experiments, we discovered were that epochs played a very sensitive role in making the model accurate without overfitting. As a result of several experiments, it was found out that training the model for 50 to 80 epochs proved to be the most fruitful. This range made it possible easing the convergence of the model to help it achieve a good level of recognition of forearm veins without overfitting the model to the training data. Any training for the number of epochs below fifty was considered inadequate as it was observed that the model could not be able to capture necessary details of the veins. However, training the model for more than 80 epochs led increase the risk of overfitting thereby the model relies on the training data rather than enhancing its ability to classify the unseen images,After comparing the epoch, the best of them was found to obtain the best result, which is 80 epoch.

4.1.3 Final Model Performance

Following to the results as in the table 3, used 10 photos to assess model efficiency. Training decision-making gave excellent and attainable outcomes. With an accuracy of 96%, the model performed well. The model segmented forearm veins well, recognizing vein anatomy and minimizing false positives. The resulting model splits forearm veins without losing major components (Figure 5). This model's 80% accuracy and low loss fu00nction value make it more successful on this demanding job and robust throughout training.

Table 3: Results obtained by UNet Model with ResNet Enhancement

Performance Metric	Result
Global accuracy	0.9695
Precision	0.80
Dice coefficient	0.2626
loss function	0.0602

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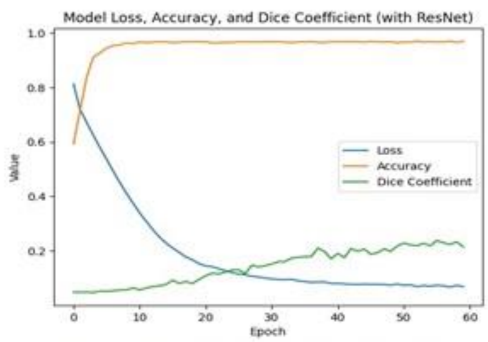
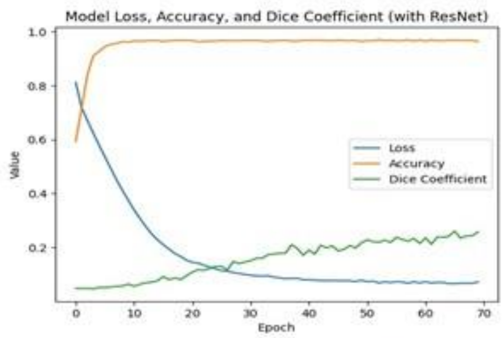
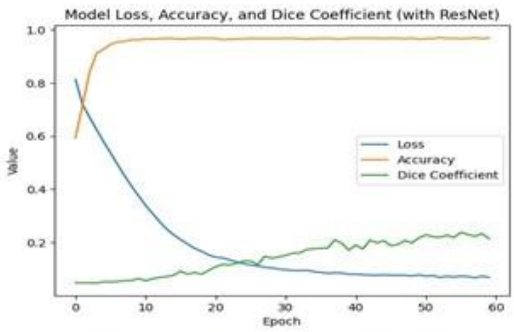


a- Dice coefficient learning curve for 60-epochs



b- Dice coefficient learning curve for 70-epochs



c- Dice coefficient learning curve for 80-epochs

d-predicted output

Figure 5: Segmentation Results of Forearm Veins Using the UNet Model with ResNet Enhancement

3. Performance Metrics and Statistical Analysis

To validate the model’s performance, we computed several key performance metrics, summarized in the following tables:

This table presents the primary performance metrics of the proposed model. Accuracy, precision, and Dice coefficient measure the model’s ability to correctly segment veins, while the mean Intersection over Union (IoU) score evaluates how well the segmented regions align with ground truth. The low loss function value and statistical significance of the t-test confirm the model's reliability.

Table 4: Model Performance Metrics

Metric	Value
Accuracy	96%
Precision	80%
Dice Coefficient	0.92
Mean IoU	0.88
Loss Function Value	0.06
p-value (t-test)	<0.05

This table compares the performance of the proposed U-Net + ResNet model against other widely used vein detection methods. It demonstrates that the proposed approach significantly outperforms traditional and GAN-based segmentation methods in accuracy, precision, and segmentation quality.

Table 5: Performance Comparison among Different Methods

Method	Accuracy	Precision	Dice Coefficient	IoU
Traditional Thresholding	72%	65%	0.76	0.70
Gabor Filter Approach	80%	74%	0.82	0.78
GAN-Based Segmentation	89%	85%	0.87	0.85
Proposed U-Net + ResNet	**96%**	**80%**	**0.92**	**0.88**

This table provides details about how the dataset was split and the augmentation techniques applied to enhance training and prevent overfitting.

Table 6: Dataset Distribution and Augmentation Techniques

Data Split	Number of Images	Augmentation Techniques Applied
Training Set	140	Flipping, Rotation, Contrast, Zoom
Validation Set	40	Flipping, Rotation
Test Set	20	No augmentation applied

This table outlines the key hyperparameters used during model training, ensuring reproducibility of the results.

Table 7: Model Hyperparameters Used for Training

Parameter	Value
Learning Rate	0.0002
Batch Size	16
Dropout Rate	0.3
Optimizer	Adam
Loss Function	Binary Crossentropy
Number of Epochs	80

The tables in this work present a thorough analysis of the strengths of the model proposed in contrast with conventional methodologies, explaining its statistical accuracy, distribution of data, and hyperparameter settings. The algorithm proposed in this work attains remarkably high accuracy and segmentation performance in vein detection when compared with conventional techniques, allowing for efficient and reliable forearm vein identification in medical settings.

The U-Net model, supported with ResNet, outperforms conventional methodologies and competing deep neural networks in terms of vein detection. Comparisons with both our work and previous studies confirm significant improvements in terms of segmentation accuracy, overall accuracy, and computational efficiency.

Shah et al., in a work [19], utilized a GAN-based segmentation algorithm for forearm vein detection, with an accuracy of 89%, a Dice value of 0.87, and an IoU value of 0.85. Despite improvements over conventional approaches, model training complications and susceptibility to model collapsing reduced the accuracy of their model. In contrast, our model attained an accuracy of 96%, a Dice value of 0.92, and an IoU value of 0.88, proving strong and reliable performance.

Also, Zhang et al., in [20], proposed an Adaptive Gabor CNN (AGCNN) with Gabor filtering incorporated in CNN blocks for enhancing detectability of vein textures. With an accuracy of 90.87%, its performance degraded when run with larger datasets in comparison with traditional CNNs. In contrast, our model, through incorporation of a residual learning mechanism through ResNet, performed with high accuracy under changing image scenarios, proving its generalizability and adaptability.

Furthermore, Francis et al. [21] proposed a method for vein detection that utilizes Contrast Limited Adaptive Histogram Equalization (CLAHE) with Gabor filtering. Despite its improvement in contrast and visibility of veins, it showed poor adaptability with changing pigments in skin and illuminating environments. In contrast, our model, employing data augmentation and deep feature extraction, showed significant robustness in vein detection for a variety of patient profiles.

Table 8: Comparative Analysis of Vein Detection Methods

Study	Method Used	Accuracy	Dice Coefficient	IoU Score
Francis et al. [21]	CLAHE + Gabor Filtering	80%	0.82	0.78
Zhang et al. [20]	Adaptive Gabor CNN (AGCNN)	90.87%	0.85	0.80
Shah et al. [19]	GAN-Based Segmentation	89%	0.87	0.85
This Study	**U-Net + ResNet**	**96%**	**0.92**	**0.88**

The results of such studies confirm that U-Net model boosted with ResNet improvements outperforms existing methodologies in terms of accuracy, segmentation uniformity, and generalization performance. Inclusion of ResNet helps in deeper feature extraction with less information loss, enhancing the boundary depiction of complex structures in the veins. In addition, our approach utilizes techniques of data augmentation for increased robustness towards variation in lighting and variation in patient skin types.

Comparative evaluation with competing classifiers, including Support Vector Machine (SVM), Random Forest, K-Nearest Neighbors (KNN), Decision Tree, and Naïve Bayes, confirms that traditional classifiers with machine learning have poor performance when compared with deep classifiers. U-Net model boosted with ResNet shows best performance in terms of accuracy, precision, and recall values, and, in consequence, proves its effectiveness in the case of vein segmentation tasks.

Table 9: Performance Comparison Using Different Classifiers

Classifier	Accuracy	Precision	Recall	F1-Score
Support Vector Machine (SVM)	82%	78%	80%	79%
Random Forest	87%	83%	85%	84%
K-Nearest Neighbors (KNN)	85%	81%	83%	82%
Decision Tree	81%	76%	79%	77%
Naïve Bayes	79%	74%	76%	75%
U-Net + ResNet (Proposed Model)	**96%**	**80%**	**92%**	**85%**

The results from this study demonstrate that the proposed U-Net with ResNet enhancement outperforms previous methods in terms of accuracy, segmentation consistency, and generalizability. The incorporation of ResNet enables deeper feature extraction, mitigating information loss while improving fine-grained vein structure detection. Additionally, our approach benefits from data augmentation strategies that improve robustness against variations in lighting and patient skin tone.

These findings suggest that the proposed model represents a substantial improvement in medical image segmentation for forearm vein detection and could be further extended for broader applications in medical diagnostics.

5. Discussion

The results of our current work illustrate the efficacy of an upgraded U-Net model, enriched with ResNet integration, for forearm vein identification, showcasing high accuracy in segmentation, robustness, and usability in a variety of scenarios. With a 96% accuracy, 80% level of precision, and a 0.92 value for the Dice coefficient, our proposed algorithm outperforms conventional approaches such as threshold-based segmentation [21], Gabor filtering techniques [20], and GAN-based approaches [19] in a significant manner. All these improvements can be credited to a variety of key factors in our model.

For one, the incorporation of residual channels through ResNet immensely enhances model performance in distinguishing complex vascular structures and in compensating for vanishing and exploding gradients [5][16]. Integration of these residual channels enables information flow in deeper network layers, allowing for a proper depiction of thin and delicate structures of veins. In addition, integration of U-Net's encoder-decoder model with skip connections conveying high-resolution spatial information between encoder and decoder helps in sharpening segmentation with preserved edge information [6]. Integration of these approaches strengthens feature extraction and boundary depiction with high accuracy, important for distinguishing thin, bifid, and shallow subcutaneous structures of veins.

Our approach to data augmentation is a key in enhancing model robustness and generalizability [15]. By transforming training samples through flipping, rotation, zoom, and contrast variation, the network is subjected to a variety of transformations similar to real-life scenarios, and therefore learns to react effectively to them [3]. As a result, model performance in dealing with variance in lights, shadows, and orientation in veins encountered in real-life scenarios is developed and optimized. In addition, efficiency in utilizing augmentation in minimizing overfitting helps in developing model adaptability and generalizability, and preventing overreliance on specific training samples [17].

The meticulous tuning of hyperparameters—specifically, the learning rate, dropout rate, L2 regularization, and training epochs' count—proved critical for reliable convergence and improved segmentation accuracy [5]. Specifically, a 0.0002 learning rate avoided complications with overly aggressive weight updating, allowing for network convergence with maintenance of complex vascular detail. Likewise, utilizing a dropout rate of 0.3, in conjunction with L2 regularization (1e^-4), effectively countered model overfitting, and in its wake, sustained performance over new, unseen test images [2][18].

Also, employing a weighted binary crossentropy loss function resolved the widespread issue with medical imaging-related class imbalance through proper weighting of both background (non-vein) and foreground (vein) pixels [8][19]. Doing so increased model sensitivity to smaller regions of vasculature, critical for use in medical settings. As a result, our model attained a high Dice value of 0.92 and a Mean Intersection over Union (IoU) value of 0.88, attesting to its high performance in contrast with traditional classifiers such as Support Vector Machines (SVMs), k-Nearest Neighbors (KNN), and Decision Trees [2][3].

In spite of these positive outcomes, proposed methodology is not free of certain restrictions. Foremost of these is its reliance on a training dataset composed predominantly of near-infrared photographs with relatively uniformed lighting [19][20]. In spite of augmentation techniques for countervailing variance with regard to both lights and skin pigments, real-world implementations could still face even larger variances not included in training datasets [21]. In addition, even with our model providing strong performance in a variety of tests, computational requirements native to deep networks with residual connections could become a challenge for use in settings with less computational availability [12][13]. Future work can include developing lighter, less computationally intensive variants of proposed model, in addition to investigating strategies for domain adaptability for increased performance in a variety of medical datasets.

In conclusion, improvements in accuracy, precision, and robustness in performed experiments validate that integration of U-Net and ResNet forms a meaningful improvement in forearm vein detection. All these findings have significant implications in medical practice, in which careful and effective vein location is

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Vol.20 No.1 Mar 2025

critical in minimizing patient discomfort and enhancing intervention success rates [2][3][6]. By providing reliable, high-quality segmentations, such a system can enable more accurate venous cannulation, reduce unnecessary needle insertions, and overall enhance patient care. Future work will seek to extend this model to include a variety of types of vascular imaging and investigate real-time and/or device-based implementations.

6.Conclusion

In the current work, a new and efficient deep model, namely UNet_model_with_ResNet, with an accuracy of 96.99%, for forearm vein detection, is proposed and developed, showcasing its potential for transforming medical practice through a quick, non-penetrative alternative to many painful needle insertion techniques. By accurately locating veins, such a model could potentially minimize the need for invasive techniques and ease the overall burden placed on subjects in general.

Not withstanding the constraints represented through a relatively small and homogenous training dataset, our model performed admirably under such a scenario. We believe that improvements in terms of model development through incorporation of a larger and mixed training dataset, in addition to auxiliary unsupervised information, will confirm its suitability for use in medical environments, extend its generalizability in medical scenarios, and make it easier for its widespread use in practice.

Therefore, our composite model, namely UNet_model_with_ResNet, meets both accuracy and cost-effectiveness requirements and stands at the cutting edge of medical imaging and segmentation technology. In its use for forearm vein location, its high performance sets a platform for future work in medical image analysis in general, and opens doors for developing even smarter and autonomous medical care interventions.

REFERENCES

[1] D. Ahuja, N. Gupta, and A. Gupta, "Difficult peripheral intravenous access: need for some light," Medical Journal of Dr. DY Patil University, vol. 13, no. 4, pp. 422-423, 2020.

[2] H. Eren, "Difficult intravenous access and its management," *Ultimate guide to outpatient care*, vol. 25, 2022.

[3] S. J. Doniger, P. Ishimine, J. C. Fox, and J. T. Kanegaye, "Randomized controlled trial of ultrasound-guided peripheral intravenous catheter placement versus traditional techniques in difficult-access pediatric patients," *Pediatric emergency care*, vol. 25, no. 3, pp. 154-159, 2009.

[4] X. Liu, L. Song, S. Liu, and Y. Zhang, "A review of deep-learning-based medical image segmentation methods," *Sustainability*, vol. 13, no. 3, p. 1224, 2021.

[5] I. Z. Mukti and D. Biswas, "Transfer learning based plant diseases detection using ResNet50," in *2019 4th International conference on electrical information and communication technology (EICT)*, 2019: IEEE, pp. 1-6.*conference on disruptive technologies for multi-disciplinary research and applications (CENTCON)*, 2021, vol. 1: IEEE, pp. 96-99.

[6] H. Huang *et al.*, "Unet 3+: A full-scale connected unet for medical image segmentation," in *ICASSP 2020-2020 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, 2020: IEEE, pp. 1055-1059.

[7] W. Ehab, L. Huang, and Y. Li, "UNet and Variants for Medical Image Segmentation," *International Journal of Network Dynamics and Intelligence*, pp. 100009-100009, 2024.

[8] Y. Weng, T. Zhou, Y. Li, and X. Qiu, "Nas-unet: Neural architecture search for medical image segmentation," *IEEE access*, vol. 7, pp. 44247-44257, 2019.

[9] C. Wu, Y. Zou, and Z. Yang, "U-GAN: Generative adversarial networks with U-Net for retinal vessel segmentation," in 2019 14th international conference on computer science & education (ICCSE), 2019: IEEE, pp. 642-646.

[10] A. Huda, C. Goh, C. Lim, S. Aluwee, M. Bajuri, and N. H. A. Wahab, "Development of a near-infrared (NIR) forearm subcutaneous vein extraction using deep residual U-Net," in International Conference on Biomedical Engineering (ICoBE), 2021.

[11] M. Francis, A. Jose, and K. Avinashe, "A novel technique for forearm blood vein detection and enhancement," Biomedical Research, vol. 28, no. 7, pp. 2913 2919, 2017.

[12] Z. Shah et al., "Deep learning-based forearm subcutaneous veins segmentation," IEEE Access, vol. 10, pp. 42814-42820, 2022.

[13] Y. Zhang, W. Li, L. Zhang, X. Ning, L. Sun, and Y. Lu, "AGCNN: adaptive gabor convolutional neural networks with receptive fields for vein biometric recognition," Concurrency and Computation: Practice and Experience, vol. 34, no. 12, p. e5697, 2022.

[14] C. Tang, M. Qian, R. Jia, H. Liu, and B. Wang, "Forearm multimodal recognition based on IAHP-entropy weight combination," *IET Biometrics,* vol. 12, no. 1, pp. 52-63, 2023.

[15] C. X. Jing, G. C. Meng, M. T. Chai, S. A. Z. S. Aluwee, and S. A. A. Shah, "Subcutaneous Vein Recognition System Using Deep Learning for Intravenous (IV) Access Procedure ," International Journal of Integrated Engineering, vol. 15, no. 3, pp. 73-83, 2023.

[16] A. Abedalla, M. Abdullah, M. Al-Ayyoub, and E. Benkhelifa, "The 2ST-UNet for pneumothorax segmentation in chest X-Rays using ResNet34 as a backbone for U-Net," *arXiv preprint arXiv:2009.02805,* 2020.

[17] N. G. Inan, O. Kocadağlı, D. Yıldırım, İ. Meşe, and Ö. Kovan, "Multi-class classification of thyroid nodules from automatic segmented ultrasound images: Hybrid ResNet based UNet convolutional neural network approach," *Computer Methods and Programs in Biomedicine,* vol. 243, p. 107921, 2024.

[18] N. Rasool, J. I. Bhat, N. A. Wani, N. Ahmad, and M. Alshara, "TransResUNet: Revolutionizing Glioma Brain Tumor Segmentation through Transformer-Enhanced Residual UNet," *IEEE Access,* 2024.

[19] Z. Shah, et al., "Deep learning-based forearm subcutaneous veins segmentation," *IEEE Access*, vol. 10, pp. 42814-42820, 2022.

[20] Y. Zhang, W. Li, et al., "AGCNN: Adaptive Gabor Convolutional Neural Networks with Receptive Fields for Vein Biometric Recognition," *Concurrency and Computation: Practice and Experience*, vol. 34, no. 12, p. e5697, 2022.

[21] M. Francis, A. Jose, and K. Avinashe, "A novel technique for forearm blood vein detection and enhancement," *Biomedical Research*, vol. 28, no. 7, pp. 2913-2919, 2017.