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# Heart Attack Risk Prediction Using Retinal Eye Images Based on Machine Learning and Image Processing

**N. Arikaran[1], S.Sriram sai[2], A. Mohamed Barseth[3], S. Visvesh[4], Arya Ejoumalai[5]**

[1,2,3,4,5,]Manakula Vinayagar Institute of Technology, Puducherry, India

Email ID: arikaran.n@gmail.com

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**ABSTRACT**

Early diagnosis of heart attacks is a critical challenge in the healthcare industry, as early diagnosis tends to result in significantly better patient outcomes. Retinal imaging has been proven to be an efficient and non-invasive diagnostic tool for cardiovascular disease, as the retina provides vascular changes indicative of heart disease. Conventional machine learning techniques, including Support Vector Machines (SVM) and Random Forests, have been applied to address this task., their efficiency is usually undermined by the heterogeneity and complexity of image data and their incapability of extracting useful features. To counter these, a deep learning model is proposed that integrates U-Net architecture has been employed for segmenting retinal images. Efficient Net for classification. U-Net up-scales the input images by outlining prominent features such as blood vessels and eliminating background noise. The up-scaled images are then subjected to Efficient Net, which is best suited for detection of complex patterns due to its optimized and scalable architecture. This integrated process enhances the model's sensitivity to detect subtle indicators of cardiovascular risk easily missed by traditional models. The system therefore provides enhanced prediction accuracy and facilitates a quicker, automated, and non-invasive diagnostic process. This makes it an effective tool for supporting early diagnosis and preventive care of cardiovascular diseases

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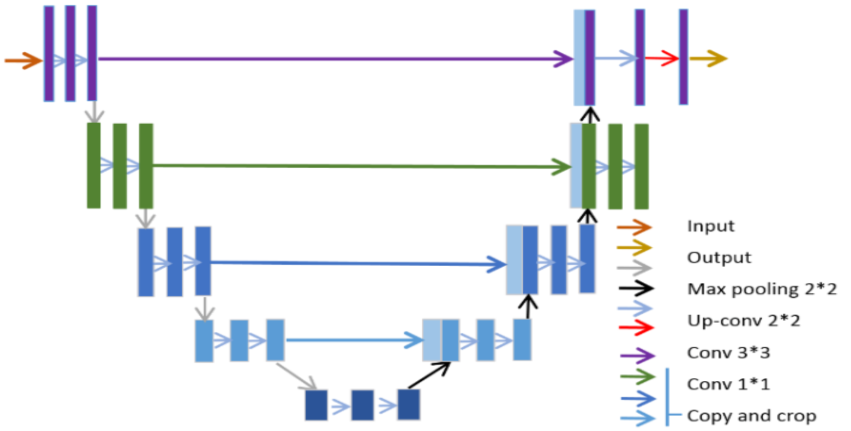
**Keyword:** *Heart attack, retinal image, U-Net, Efficient Net, deep learning, classification, segmentation, prediction, medical imaging, diagnosis*

## 1. INTRODUCTION

Heart disease prediction through retinal imaging is a growing field that utilizes the eye’s vascular structure to assess cardiovascular health. The retina contains a dense network of blood vessels, and any abnormalities—such as thickening, narrowing, or unusual branching—can reflect underlying heart conditions[]. This method is non-invasive and offers a unique window into the body’s vascular system without the need for complex procedures like ECG or blood tests. Artificial Intelligence (AI), particularly plays a key role in retinal image analysis by leveraging deep learning models like Convolutional Neural Networks (CNNs). These computer vision systems are trained on large image databases to detect subtle vascular changes—such as tiny swellings or hemorrhage in the retina—potentially indicative of underlying heart-related medical conditions. AI can process huge amounts of retinal images at velocity and identify patterns too fine to the human eye, enabling early detection and treatment. AI-powered retinal exams are said to be able to diagnose health factors such as hypertension and possible heart attack risk with effectiveness. Despite the high potential of the method, the method still has to overcome challenges like inconsistent image quality and the requirement for huge amounts of labeled data. Nonetheless, with ongoing improvements in technology, retinal imaging can become a routine screening practice, providing a quick, inexpensive, and efficient means of forecasting heart disease, and revolutionizing cardiovascular care.

### *A. UNET:*

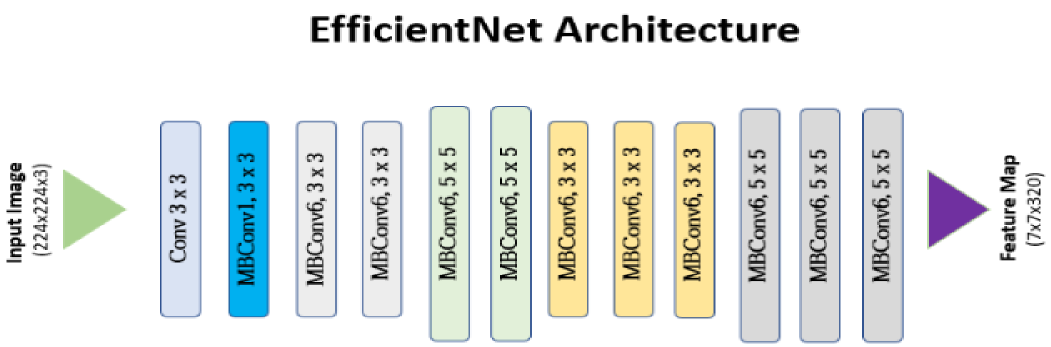
U-Net is a widely used deep learning architecture for image segmentation, particularly in medical applications. Its structure is in the form of a "U" and consists of two main components: the encoder and the decoder. The encoder is responsible for down sampling the input spatial information of the input step by step and extracts necessary features via convolution and pooling operations. This allows the model to understand the overall structure and context of the image. The decoder then rebuilds the image’s original size using upsampling techniques. It also uses skip connections to bring in detailed information from the encoder layers, which helps in producing accurate and detailed segmentations.




Skip connections within the U-Net structure are essential to preserve fine spatial information that may be destroyed through down sampling. The skip connections facilitate the merging of low-level and high-level features, increasing the precision of the output. A 1×1 convolution the network concludes with a dedicated output layer. to generate the final segmented image. U-Net can handle sparse training data due to its capability to fuse context with accurate localization. This renders it particularly suitable for medical image tasks like indicating retinal vasculature, identifying irregularities, or isolating organs within diagnostic images.

### B. ARCHITECTURE OF EFFICIENTNET:

EfficientNet is a deep learning model built using MBConv blocks, which are efficient and lightweight due to depthwise separable convolutions and shortcut connections. It begins with a stem convolutional layer to process the input, followed by several stages of stacked MBConv blocks. These blocks progressively increase channel depth and reduce spatial resolution, Such a structure allows the model to take in complex, hierarchical features economically while minimizing the use of resources. Its potential to preserve high accuracy at less computational expense renders EfficientNet more than ideally suitable for tasks such as medical image classification.




Efficient Net has its distinctive compound scaling approach that scales the architecture's depth, breadth, and input image resolution evenly with a single scaling factor. It starts with a base model EfficientNet-B0 and then scales up to larger models such as B1 up to B7. In the later stages, the architecture incorporates a global average pooling layer. followed by a fully connected layer to produce the final output. This carefully crafted architecture enables Efficient Net to have high accuracy with low computational and memory costs.

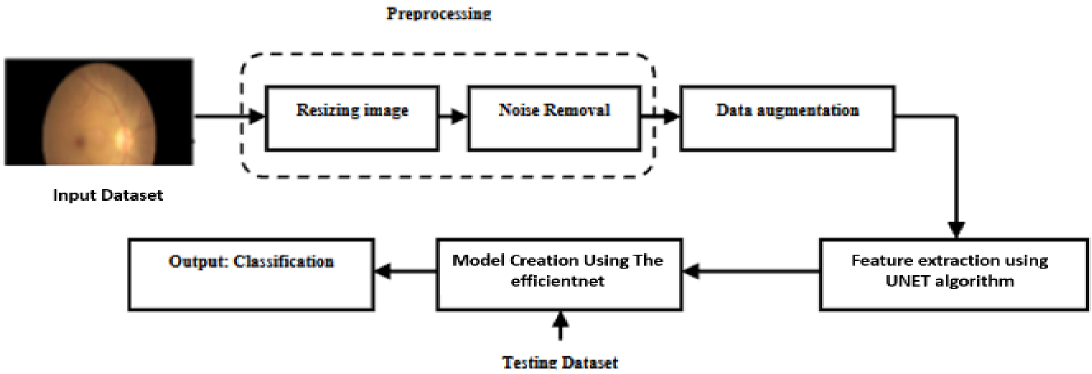
## 2. LITRATURE SURVEY:

***[1] SibghaTaqdees [1]*** Heart disease forecasting is of great significance in the healthcare sector by allowing early diagnosis and minimizing mortality. There are some of the machine learning techniques used in this field. Although these models offer benefits of simplicity and interpretability, they tend to be characterized by poor accuracy, overfitting, and high computational complexity. Moreover, most of them depend on invasive techniques, including blood samples or ECGs, which can obstruct their feasibility and availability. To address these challenges, newer studies are exploring non-invasive image-based techniques using retinal scans, as the condition of the retina's blood vessels can provide useful clues about heart health.The retina can serve as a valuable indicator of cardiovascular health. With advancements in technology, deep learning models like U-Net (for segmenting retinal images) and EfficientNet (for classifying extracted features) are increasingly being used to study these retinal patterns. These modern techniques provide better accuracy, stronger generalization, and offer a non-invasive and affordable method for large-scale heart disease detection. This approach has the potential to make heart health screening more accessible. This study focuses on building a machine learning-based system aimed at identifying individuals who may be at risk of developing heart conditions.In this approach, two popular classification methods — k-Nearest Neighbors (KNN) and Logistic Regression are widely used to model patient information to predict the likelihood of heart disease. The model proved to show encouraging results by combining the benefits of both approaches. KNN was able to categorize patients efficiently based on similarity in their medical history, whereas Logistic Regression aided in the calculation of heart disease probability while Logistic Regression offered reliable predictions by estimating the likelihood of disease presence. The combined use of these algorithms delivered good accuracy in identifying individuals who may be at risk. However, the study mainly relies on structured data that includes clinical values like blood pressure, cholesterol, and glucose levels, which are typically obtained through invasive proceduresWhile the study achieved decent accuracy, it did not extensively explore how the model performs on larger or more varied datasets, nor did it consider the use of non-invasive data sources, suggesting opportunities for future enhancements. This research lays a strong groundwork for applying machine learning in the medical field, while also highlighting the need for more scalable and advanced methods for accurate, non-invasive heart disease prediction.In another study by researchers like Kelvin Kwakye and E. Dadzie, the focus was on designing and when evaluating machine learning classification models to assess the risk of coronary heart disease, a critical challenge was dealing with imbalanced datasets and irrelevant features, both prevalent in medical data. To address this challenge, they used SMOTE (Synthetic Minority Over-sampling Method) to modify class distributions applied feature selection methods to keep only the most important data points. These preprocessing techniques helped improve the sensitivity and recall of the models—key factors in reducing false negatives during medical diagnosis. The models also showed better computational speed, making them suitable for situations that require quick and accurate decisions. However, some limitations still remain, leaving scope for further refinement.

The models considered a relatively narrow range of features, potentially reducing their ability to capture the complexity of coronary heart disease risk factors. This limitation suggests room for improvement in integrating additional physiological, demographic, or imaging data for more comprehensive predictions. ***[4] GhulabNabiAhmad, HiraFathima, Shafiuallah [4]*** This study seeks to develop an efficient heart predictive algorithm for disease using a combination of machine learning methods and logistic regression models. The method entails assessing the performance of predictive models based on a combined dataset and applying the train-test split techniqueto ensure model validation. By leveraging high-resolution datasets, the study aims to enhance the reliability of predictions and improve classification accuracy.Logistic regression is applied in the algorithm to effectively catch up on the relationship between input attributes and heart disease likelihood. Using a combined dataset, the model is augmented with a wider variety of patient information, providing a stronger base to make predictions.The study highlights the capability of regression models to offer interpretable insights into the factors influencing heart disease risk. ***[5]*** *MohammadTabrez Quasim [5]* Oral cancer is a serious health concern globally, especially in low- and middle-income nations, where it contributes to high mortality rates. Early detection is key to enhancing patient outcomes through facilitating early treatment and prevention. Consequently, there is an increasing demand for automated diagnostic systems to assist healthcare workers in this endeavor. Routine dental check-ups are essential for identifying symptoms at an early stage. This work presents a new technique for early oral cancer detection that takes advantage of the mouth's distinct sensory landscape. This technique utilizes the information processed by deep neural networks, specifically to identify intricate patterns tied to the disease. Using transfer learning, a method where pre-trained models of related tasks are used, the model is fine-tuned for the task of oral cancer detection. Transfer learning models were experimented and compared, and the optimal learning rate for accurate classification was discovered. Among the models that were evaluated, Inception-V3 proved to be most accurate, and thus deep learning methods are found to be promising in solving this complex medical condition. One of the challenges that have been identified in the study is the model's slower processing speed, which could be due to the high-resolution data and the computational complexity of dealing with large datasets. In spite of this limitation, the method has a lot of potential for enhancing the accuracy and effectiveness of diagnosing heart disease

### *A. ARCHITECTURE DIAGRAM:*

The framework of the proposed heart attack detection system is built to take advantage of deep learning techniques, aiming for precise and early identification by analyzing retinal images.The system begins with the acquisition of high-quality retinal images, which serve as the input. These images often contain noise and irrelevant background information that can hinder effective analysis. To address this, the first stage involves a U-Net framework, which is among the most widely used CNN architectures, is specifically designed to be used for image segmentation problems. It undergoes retinal images to feature extract and enhance major vascular features while at the same time decreasing noise and minor details. That way, it only keeps most important features available for subsequent analyses. Once they are segmented, the improved images, which contain relevant features, are then sent to the EfficientNet model to classify them.EfficientNet, known for its optimized scaling of depth, width, and resolution, effectively extracts complex spatial patterns and subtle indicators of cardiovascular disease present in the segmented images. It learns to differentiate normal and abnormal retinal characteristics that may suggest the possibility of a heart attack. This integration enables the system to concentrate on the most important regions of the image, enhancing the precision of classification




The Framework final output provides a prediction of the heart attack risk, derived from the analysis of retinal features. This comprehensive workflow—from acquiring images and preprocessing them using U-Net, to extracting features and classifying with EfficientNet, leading to the final prediction—creates a strong architecture that improves diagnostic accuracy. The design promotes automation, minimizes eliminates the requirement for manual feature extraction and facilitates non-invasive early detection, making it an essential tool in preventive healthcare.

### *Proposed approach:*

The suggested system is a sophisticated deep learning model developed to assess heart attack risks based on retinal images. It employs a two-stage architecture combining U-Net for image segmentation and EfficientNet for classification. Retinal images are non-invasive and provide valuable insights into cardiovascular health, but they often contain noise and irrelevant features. To improve analysis, U-Net is first applied to these images, effectively segmenting and highlighting critical features like blood vessels, while masking unnecessary information. This preprocessing step enhances the image quality, ensuring only relevant features are passed on for classification. The segmented image output from U-Net is subsequently passed through EfficientNet, a deep learning model known for its efficient scalability and deliver strong performance in medical image analysis. EfficientNet analyzes the enhanced retinal images to detect subtle patterns and abnormalities that could signal a heart attack risk. Its optimized architecture allows for precise feature extraction, making it superior to traditional machine learning models in capturing intricate spatial details. By integrating U-Net and EfficientNet, the system achieves higher accuracy and robustness in cardiovascular risk prediction. This fully automated, non-invasive diagnostic pipeline aids clinicians by providing reliable early detection, improving patient outcomes and supporting preventive healthcare through timely intervention.

### *DATA GATHERING:*

Data collection is the first and essential step in building a reliable deep learning model. In this project, the focus is on collecting high-quality retinal fundus images, which serve as the primary data source for predicting heart attack risks. These images are captured using non-invasive imaging equipment and can can be obtained from publicly accessible datasets (e.g., DRIVE), STARE, or Messidor) or By partnering with healthcare institutions, there should be diversity in the dataset, with variation in age, gender, ethnicity, and illnesses ‘ The gathered dataset should include labels indicating whether each patient has cardiovascular risks or a history of heart-related conditions. These labels may come from clinical diagnoses or electronic health records. Along with the images, associated metadata such as age, blood pressure, or cholesterol levels could enhance model performance but must be handled carefully for privacy and ethical reasons.The performance of the model is largely dependent on the quality of data. Poorly labeled, low-resolution, or blurry images can lead to poor performance and wrong predictions. Therefore, it is important to validate and clean the data extensively. Moreover, patient consent, data anonymization, and compliance with ethical standards (such as HIPAA or GDPR) must be ensured, especially when using clinical data. Data augmentation techniques may also be used at this stage to artificially increase the dataset size, which helps in training deep learning models more effectively.

### *Pre-processing*

Pre-processing prepares the raw retinal images for further analysis and helps Enhance model performance by standardizing the data, making it more consistent and easier to interpret. Raw medical images often differ in size, brightness, contrast, and clarity, so they must be standardized before inputting into the neural networks. First, All images are adjusted to a uniform resolution (e.g., 224x224 or 512x512 pixels) to align with the input size requirements of EfficientNet and U-Net. Following this, normalization is performed to scale pixel values into a normalized range, often between 0 and 1, stabilizes the training process and accelerates convergence. Reducing noise using methods like Gaussian filtering or median blurring can be used to eliminate redundant background pixels and improve the definition of critical features within an image..To improve the dataset further, data augmentation techniques like flipping, rotating, cropping, and zooming are applied. These methods create variations in the training data, making the model more resilient and reducing the likelihood of overfitting. Additionally, techniques like histogram equalization or contrast enhancement can be used to emphasize key features such as blood vessels and optic discs.

Segmentation is an important pre-processing step wherein the image is conditioned for fine feature extraction using U-Net. The primary objective of this stage is to ensure that the images input into the model have consistent quality and emphasize the most important information, thereby improving the model's learning and prediction accuracy in subsequent stages.

***Feature Extraction Using U-Net:***

Feature extraction is a vital stage where the model identifies and enhances specific patterns or regions in an image that are most relevant to the prediction task. In this project, **U-Net** is employed for this purpose, particularly to highlight the blood vessels (referred to as "vines") in retinal images. These vessels carry crucial information about the cardiovascular system and can reflect early signs of systemic issues like hypertension or atherosclerosis, which are closely linked to heart attack risks.U-Net is a CNN architecture, which was specifically developed for biomedical image segmentation. U-Net has both an encoder (contracting path) and decoder (expanding path) with skip connections to preserve spatial details during the up sampling.This structure allows the model to efficiently learn how to segment the input image, isolating structures like blood vessels while filtering out irrelevant details.During training, U-Net is fed pairs of input images and their corresponding annotated masks (manually labeled by medical experts or generated through semi-automated tools). The model learns to associate the input image with its corresponding segmentation mask, and after training, it can accurately generate masks for new, unseen images. Once U-Net has segmented key features, such as blood vessels, in the retinal image, the resulting mask is combined with the original image to create a clearer, more focused version. This enhanced image is then passed to EfficientNet for the classification step. By concentrating on the most relevant areas, U-Net improves feature extraction quality and significantly boosts the system's overall prediction accuracy.

***MODEL CREATION USING EFFICIENTNET:***

the Once the retinal images are segmented and processed with U-Net, they are fed into EfficientNet, which is a latest-generation convolutional neural network known to perform well on image classification. EfficientNet is known for achieving top accuracy on image recognition benchmarks while being significantly smaller and faster than traditional models like ResNet or VGGEfficientNet achieves high performance by using compound scaling, a method that proportionally increases the network’s depth, width, and input size, allowing it to perform better with fewer resources. In this approach, EfficientNet is applied to determine if The model evaluates the risk of a heart attack by looking at the processed retinal image. It accepts the purified image as input and goes through several layers, such as convolution layers, batch normalization, activation functions (such as Swish), and pooling operationsThese layers help extract detailed and The model captures high-level features of the retinal image, including both subtle and large patterns. The labeled data is split for training and validation. Training employs a loss function, such as binary cross-entropy, and performance is evaluated using metrics like accuracy, precision, recall, and AUC-ROC. Transfer learning can be used by initializing the model with pre-trained weights from ImageNet, which fastens the training process and improves performance, particularly when working with limited medical data. EfficientNet is especially effective because it can spot intricate patterns while keeping computational efficiency. It identifies features in retinal images, including vessel shapes and branching patterns, that are predictive of heart health, and so is an appropriate selection for medical diagnosis, where speed as well as accuracy is essential.

***Test Data:***

Once the training is complete, the model is assessed using a separate set of images known as test data. it has never seen before—to verify how well it generalizes to new, real-world cases. The test dataset is processed using the same pipeline: images are preprocessed, segmented using U-Net, and then classified by EfficientNet. Maintaining consistency during Evaluation is important in determining the extent to which the model can generalize to actual clinical situations. To measure its performance, accuracy, precision, recall, and F1-score are computed using the test dataset. A confusion matrix is usually used to display the number of correct and incorrect predictions, such as true positives, true negatives, false positives, and false negatives. Also, ROC curves and AUC scores are utilized to evaluate the capacity of the model to separate between classes for a variety of different decision thresholds.Testing plays a crucial role in uncovering areas where the model may struggle. If it consistently mislabels specific kinds of images, this could indicate imbalances or missing patterns in the training dataset. To address this, collecting more diverse data or applying data augmentation techniques may be needed. Overall, testing ensures that the model is dependable, performs well, and is suitable for use in real-world clinical applications.

***Prediction:***

The final step is prediction, where the trained system is used to analyze new retinal images and predict whether a patient is who may have a potential risk of experiencing a heart attack. The method proceeds through the following stepssame pipeline: pre-processing the input image, segmenting relevant features using U-Net, and classifying the result using

EfficientNet. The output is typically a binary label (risk/no risk) along with a confidence score that indicates how certain the model is about its prediction. These predictions can be integrated into a clinical workflow, where doctors use them alongside other medical data to make informed decisions. The system can act as a decision support tool, alerting physicians to patients with elevated risk who might need additional medical evaluationor intervention. It can also be used in screening programs to identify at-risk individuals early, potentially preventing serious cardiovascular events. Overall, this deep learning-based prediction system offers a fast, automated, and accurate method for detecting heart attack risks, supporting the move toward more proactive and preventive healthcare.

## 3. RESULT AND DISCUSSION

"The deep learning model integrating U-Net for preprocessing and EfficientNet for classification was tested using an independent set of retinal images to measure its capacity to predict heart attack risk. The performance tested well, with EfficientNet showing high recall, precision, and F1-score, proving efficient in classification tasks. The preprocessing with U-Net greatly enhanced the quality of the input images by emphasizing significant retinal features, including blood vessels. This optimization enabled the classification model to focus on the most useful regions, eliminating noise and maximizing prediction accuracy. Additionally, the model's Area Under the ROC Curve (AUC) demonstrated exceptional performance in distinguishing between normal and high-risk cases.

The combination of U-Net and EfficientNet demonstrated superior performance compared to using either model individually or relying on conventional machine learning methods. U-Net enhanced image quality, while EfficientNet excelled at extracting deep features while maintaining computational efficiency[10]. A comparative analysis revealed that this integrated system outperformed traditional CNN models Both in terms of efficiency and accuracy of processing, the model performed well. It also maintained consistent performance on different image qualities and patient groups, revealing its good generalization ability. All these findings highlight the efficacy of deep learning in detecting subtle features from retinal images that may go undetected by human evaluators or traditional classifiers.

Although the findings were promising, some limitations were observed. The performance of the system was influenced by the quality and diversity of the training data. For instance, images with extreme lighting variations, resolution differences, or anatomical abnormalities at times resulted in incorrect predictions. Furthermore, wider clinical validation using real-world datasets is required to evaluate its full potential in healthcare settings. In spite of these limitations, the system holds tremendous promise as a non-invasive, With additional improvements and extensive testing, an automated tool for the early identification of heart attack risks could be incorporated into clinical procedures to promote proactive cardiovascular care and early diagnosis.

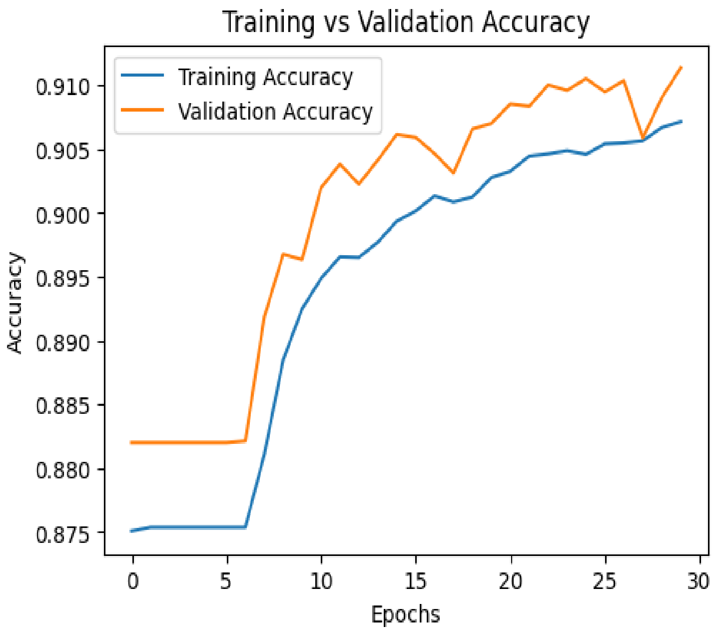
**ACCURACY :**

The deep learning model, which integrates U-Net for image segmentation and EfficientNet for classification, shows robust performance in precisely predicting heart attack risks from retinal images. During the testing stage, the model had high accuracy, meaning that the majority of its predictions were accurate. This success can be attributed largely to U-Net's preprocessing, which effectively highlights key retinal features such as blood vessels, allowing EfficientNet to focus on the most important areas for classification. The model's reproducibility over a range of test images demonstrates its robustness and capacity for generalization. This degree of accuracy confirms the model's efficacy and highlights its potential for application in practical medical diagnostics, where prompt and precise risk assessment is essential.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Predictions}} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- **TP** = True Positives (correctly predicted positive cases),
- **TN** = True Negatives (correctly predicted negative cases),
- **FP** = False Positives (incorrectly predicted as positive),
- **FN** = False Negatives (incorrectly predicted as negative).




A comparison of a deep learning model's training and validation accuracy over 30 epochs is shown in the graph above. The y-axis displays accuracy values that range from roughly 0.875 to just over 0.910, while the x-axis shows the number of epochs. The training accuracy is shown by the blue line, and the validation accuracy is shown by the orange line. The model is still learning to extract important features from the retinal images, as evidenced by the relatively low training and validation accuracies in the first epochs (roughly 1–7). Both metrics, particularly validation accuracy, show a discernible improvement starting around epoch 8, indicating that the model is starting to generalize more effectively to unknown data. Both training and validation accuracies rise gradually between epochs 10 and 30, with sporadic minor oscillations in the validation line that are probably due to chance changes in the validation set. The gap between the training and validation accuracy lines is quite minimal throughout, and this implies that the model is not overfitting and is generalizing fairly well. By the last epoch (30), training accuracy is just over 90.6%, The effectiveness of the suggested deep learning system is demonstrated by the slightly higher validation accuracy, which is approximately 91.1%. The model can accurately predict new, unseen retinal images thanks to the highly optimized combination of EfficientNet and U-Net. This approach holds great promise as a solution for classifying heart attack risks based on medical imaging.

***B. LOSS:***

In deep learning, loss is the discrepancy between the predicted outputs of the model and the true target values. It measures the error in the predictions of the model, giving useful feedback during training. The higher the loss, the more inaccurate the predictions are, and the lower the loss, the more accurate the predictions are. The loss function is essential to tracking the model's accuracy in patient classification in this retinal image-based heart attack risk prediction project. By using optimization techniques like gradient descent, the model aims to reduce this loss during training, increasing its performance with each epoch.

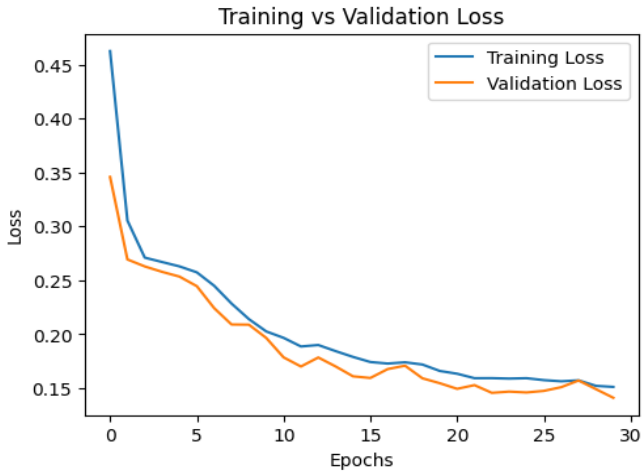
Because the model's parameters are still being adjusted, the loss is typically high during the first training phases. The loss usually drops as training goes on, indicating that the model is beginning to identify patterns in the data. Overfitting may be indicated, though, if the validation loss rises while the training loss keeps declining. In this situation, the model may find it difficult to generalize to new, unseen data since it has become unduly specialized to the training set. Conversely, it indicates that the model is learning efficiently and generalizing well if both the training and validation losses steadily decline.

$$\text{Loss} = -\sum_{i=1}^{n} y_i \log(\hat{y}_i)$$

Where:

- $y_i$ is the true label (usually 0 or 1 in binary or one-hot encoded form),
- $\hat{y}_i$ is the predicted probability for class $i$,
- $n$ is the total number of classes.

This function measures how much each class's predicted probability differs from the actual distribution. When the model is both accurate and confident, the loss is low; but if the model is confident but mistaken, the loss is high. For example, predicting a 0.9 probability for the correct class yields less loss, but predicting a 0.1 yields a much greater loss. In the proposed combined system of U-Net and EfficientNet, the loss continuously reduces over epochs, which represents better model performance with timeindicates. This implies that the model's comprehension is progressively getting better to make accurate predictions by reducing classification mistakes. Tracking the loss prevents overfitting, which allows the model to generalize well to new retinal images and eventually increase the precision of heart attack risk prediction




"The 'Training vs Validation Loss' graph illustrates the decline in loss values model is at an early learning phase. With advancing training, the losses, however, begin decreasing significantly The graph shows the loss values over time for both the training and validation datasets over 30 epochs. The y-axis displays the loss values, while the x-axis indicates the number of epochs (iterations). The validation loss is shown by the orange line, and the training loss is shown by the blue line. In the initial epochs (roughly 0 to 5), the losses are relatively high, with the training loss above 0.45 and the validation loss around 0.35, as the meaning the model is beginning to perceive significant patterns within the data. Around epoch 10, both the losses of the training as well as validation datasets continue falling steadily, plateaus at epoch 30, with steady declining, falling below 0.15. Observably, the validation loss remains comparable to or slightly less than the training loss throughout most of the training, which suggests the model isn't overfitting and generalizes well to novel data. The trend of losses indicates the power of blending U-Net and EfficientNet since the model efficiently learns the features from the retinal images with little error while enhancing the accuracy of its classifications..

***PRECISION***

Precision is an important measure of performance in classification problems, particularly in areas such as medicine where false positives can be particularly costly. The model's ability to precisely identifyThe percentage of correctly identified positive instances among all instances predicted to be positive is known as precision. It is expressed mathematically as follows: patients who are

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Based on the model's successful predictions, this formula assesses its performance. higher precision score is, the fewer false positives the model makes, which is particularly important in medicine. Misdiagnosing a healthy patient as being at risk could lead to unnecessary stress, additional testing, or treatments. In the context of the system proposed — which uses U-Net for preprocessing retinal images and EfficientNet for classification — precision reflects The model's ability to precisely identify patients who are genuinely at risk of heart attacks. If the model predicts that a person is at high risk, precision tells us how often that prediction is right. This is particularly important in healthcare because over-predicting risk

This could lead to a significant number of false positives, wasting medical resources and possibly causing harm through unnecessary interventions.In the validation phase of this system, maintaining High accuracy means that the model is correctly flagging potential heart attack risks without compromising reliability. This is in line with the goal of providing accurate, early diagnoses via retinal imaging. In situations where early detection is vital, accuracy ensures that the identified cases are significant and actionable. Consequently, the blend of precision and high accuracy supports the system's reliability for real-world medical application, enabling physicians to rely on the AI's judgment and eventually end up enhancing patient outcomes.

***RECALL***

In classification tasks, recall—also referred to as sensitivity or the true positive rate—is a crucial metric, particularly in medical diagnostics where failing to detect a true positive could have dire consequences. It assesses how well the model can detect every real positive instance. In other words, it assesses how accurately the model identifies actual positive cases. The formula for recall is:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Where:

- **True Positives (TP)** are correctly predicted positive cases,
- **False Negatives (FN)** are actual positive cases that the model failed to identify.

In the proposed system using U-Net and EfficientNet for heart attack risk prediction from retinal images, recall is especially critical. A high recall value shows that the system efficiently detects most of the people who are actually at risk. Conversely, if the model has poor recall, it might miss true instances of heart disease, thereby postponing life-saving treatments that are essential.Therefore, achieving a high recall ensures that very few true at-risk patients are overlooked, supporting early diagnosis and prevention. While high recall is desirable in healthcare applications, it often comes with a trade-off. A model can increase recall by predicting more positives, but that may lower precision if many of those positives are incorrectBalancing both precision and recall is crucial, which is why metrics like the F1 score are often used. In this deep learning system, prioritizing recall ensures that the model doesn't overlook potential cardiovascular risks, making it a dependable tool for medical screenings and early interventions.

***F1SCORE***

When there is a class imbalance or when false positives and false negatives are equally important, the F1 score provides a balanced assessment by combining precision and recall into a single metric.. The measure is particularly important in applications such as the prediction of heart attack, where accurate identification of true positives must be achieved with minimum false alarms. The F1 measure is obtained as the harmonic mean of recall and precision, as both need to be balanced. The F1 score formula is:

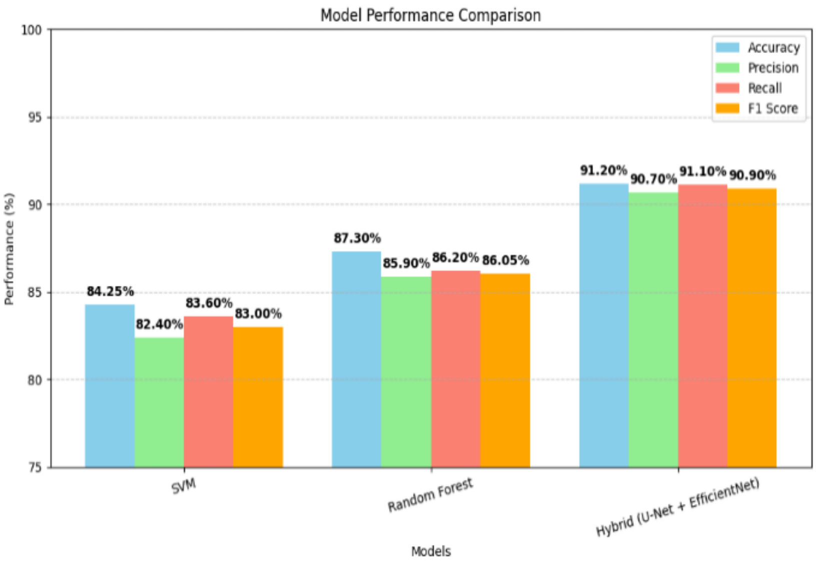
$$\textbf{F1 Score} = 2 \times \frac{\textbf{Precision} \times \textbf{Recall}}{\textbf{Precision} + \textbf{Recall}}$$

In the suggested deep learning system incorporating U-Net for image preprocessing and EfficientNet for classification, When assessing a model's performance, the F1 score is crucial, particularly when recall and precision are both significant. A higher F1 score shows that the model avoids bias toward either positive or negative outcomes and consistently produces accurate predictions using a balanced approach. This balance is especially important in medical diagnosis, where missing a high-risk patient (false negative) can lead to serious consequences, while false positives (incorrectly identifying a healthy patient as being at risk) can lead to unnecessary stress and medical interventions.

Assessing the F1 score ensures that the model performs well across multiple metrics, rather than excelling in just one area. In real-world healthcare applicationsDependence solely on accuracy can be deceptive, particularly with skewed datasets in which one of the classes prevails. For instance, assuming 95% of patients are healthy and all patients are predicted to be healthy, the model can have high accuracy but also will not catch most of the at-risk patients, resulting in low recall and an F1 score close to zero Therefore, a high F1 score in this heart attack prediction model indicates a reliable and balanced system that minimizes It is better suited for use in actual clinical settings because it successfully balances false positives and false negatives.

***Comparison graph***

The above bar chart illustrates the comparison of three models' performance—SVM (Support Vector Machine), Random Forest (RF), and Hybrid Model (U-Net + EfficientNet)—over four most important parametersThe best technique for predicting heart attacks using retinal images is determined by evaluating and comparing models using metrics like Accuracy, Precision, Recall, and F1 Score. With an accuracy of 84.25%, precision of 82.40%, recall of 83.60%, and F1 score of 83.00%, the SVM model performs admirably. SVM works well for tasks involving binary classification, but, it suffers when dealing with high-dimensional data such as retinal images since it has a limited capacity to handle intricate spatial features.




Random Forest model outperforms SVM with an accuracy rate of 87.30%, a precision of 85.90%, recall of 86.20%, and an F1 measure of 86.05%. By merging the output of multiple decision trees, Random Forest improves prediction accuracy. However, similar to SVM, RF lacks advanced feature extraction methods required for medical image analysis. On the other hand, the Hybrid Model, which integrates U-Net for preprocessing (highlighting retinal blood vessels and minimizing noise) and EfficientNet for classification, demonstrates a significant performance boost. The model has 91.20% accuracy, 90.70% precision, 91.10% recall, and an F1 score of 90.90%. The improved performance is a result of U-Net's accurate segmentation of major features and EfficientNet's scalable architecture, which detects intricate patterns in the processed retinal images. The chart clearly illustrates that the hybrid deep learning methodology provides better results in medical diagnostics, providing more predictive accuracy and aiding clinical decision-making through stable identification of cardiovascular risks from retinal scans.

## 4. CONCLUSION

In summary, the suggested deep learning system represents an improvement in identifying heart attack risk using retinal image analysis. It breaks through the drawbacks typical of conventional machine learning methods such as Random Forests and Support Vector Machines (SVM) which often struggle with complicated image data and faint visual characteristics, the hybrid approach here presents a more precise and dependable diagnostic device. By incorporating With the use of "The Efficient Net model for dependable classification tasks and the U-Net architecture for image segmentation, the system is better able to extract meaningful features from noisy and heterogeneous retinal images for more accurate predictions. This innovative approach not only improves the clarity of diagnostic information but also automates the detection process, making it faster and more reliable. This demonstrates the potential of deep learning to improve healthcare, especially in the form of non-invasive techniques for early cardiovascular risk assessment. Strong accuracy, precision, recall, and F1 score results indicate that the system may be useful in clinical settings. This study also identifies the revolutionary potential of AI-powered solutions to transform preventive healthcare. By enabling early intervention through precise, non-invasive screening, the proposed model could significantly contribute to reducing mortality rates and enhancing outcomes in heart disease management. Future improvements could focus on integrating multimodal data, such as ECG and patient history, to boost prediction accuracy. Developing a real-time diagnostic tool or mobile app would also improve clinical utility. Incorporating Explainable AI (XAI) could enhance the transparency Educating healthcare professionals about the model's decision-making process can foster trust. The accuracy and dependability of the system can be increased by utilizing larger, more diverse datasets and expanding it to detect additional diseases. Furthermore, federated learning enables various healthcare organizations to train models jointly while maintaining the privacy of patient data

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