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Original Article

Detection of Cardiovascular Diseases in ECG Images Using Machine Learning and Deep Learning Methods

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Abstract

Cardiovascular conditions (CVDs) are a major global health challenge and the leading cause of mortality worldwide. Early opinion and effective bracket of these conditions can significantly reduce losses. Electrocardiograms (ECGs), as a readily available and cost-effective individual tool, give critical perceptivity into the electrical exertion of the heart, enabling the identification of CVDs. This exploration focuses on using deep literacy models to prognosticate four distinct cardiac conditions irregular twinkle, myocardial infarction, a history of myocardial infarction, and normal heart function, exercising a intimately accessible ECG image dataset. Originally, transfer literacy was explored using pretrained models similar as SqueezeNet and AlexNet. latterly, a custom- designed convolutional neural network(CNN) was developed to enhance the discovery of cardiac abnormalities. also, these pretrained networks, along with the proposed CNN, were employed as point birth mechanisms for machine literacy algorithms, including support vector machines(SVM), K- nearest neighbors(K- NN), decision trees(DT), arbitrary timbers (RF), and Naïve Bayes(NB). The findings reveal that the proposed CNN armature surpasses being styles, achieving an delicacy of 98.23, a recall rate of 98.22, a perfection score of 98.31, and an F1 score of 98.21. also, when used as a point extractor, the CNN model achieved an emotional delicacy of 99.79 with the Naïve Bayes algorithm.

Impact Statement *— The integration of artificial intelligence (AI) into healthcare has the implicit to revise complaint discovery, significantly perfecting patient issues. This study introduces a feather light and effective CNN model that achieves 98.23delicacy in classifying cardiovascular conditions using ECG image data. The model operates efficiently on standard computing tackle, making it practical for real- world operations. Likewise, its use as a point birth tool enhances traditional machine literacy ways, delivering a remarkable 99.79 delicacy with the Naïve Bayes classifier. This approach holds pledge for IoT healthcare ecosystems, paving the way for farther exploration in AI- driven cardiovascular diagnostics.*

Introduction

Cardiovascular conditions, generally known as heart conditions, are the leading cause of death encyclopedically, as reported by the World Health Organization. These conditions claim roughly 17.9 million lives annually, counting for 32 of all deaths worldwide. Among these losses, around 85 result from myocardial infarctions (MIs), or heart attacks. Beforehand discovery and opinion of cardiovascular conditions can significantly reduce mortality rates. Colorful individual ways, including electrocardiograms (ECGs), echocardiography, cardiac glamorous resonance imaging (MRI), reckoned tomography, and blood tests, are extensively employed in healthcare settings. Among these, ECGs stand out as a cost-effective and noninvasive tool for assessing heart exertion and relating heart- related issues. Still, counting solely on homemade interpretation of ECGs by medical experts can be time- consuming and prone to inaccuracies.

The integration of artificial intelligence (AI) in healthcare offers significant eventuality for minimizing medical crimes. Machine literacy (ML) and deep literacy (DL) ways, in particular, are decreasingly being employed for the automated vaticination of heart conditions. Machine literacy generally involves a point birth and selection process, where applicable data features are linked and reused before bracket. Point birth reduces the dimensionality of data while retaining essential information, with styles like top element analysis being extensively used. Point selection, on the other hand, eliminates inapplicable or spare features and is distributed as supervised or unsupervised.

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Supervised point selection styles include sludge, wrapper, and bedded approaches.

Abstract conception of machine literacy and deep literacy.

Colorful machine learning algorithms have been applied to prognosticate cardiovascular conditions. For case, Soni et al. compared algorithms like decision trees (DT), Naïve Bayes (NB), K- nearest neighbors (KNN), and neural networks (NN), achieving the loftiest delicacy of 89 with DT. also, Dissanayake and Md Johar estimated the impact of point selection on machine literacy classifiers using ways similar as ANOVA, Chi-square tests, and Lasso retrogression. Their study demonstrated bettered vaticination delicacy with styles like backward points election combined with DT classifiers. Other studies, similar as those by Kim et al., have explored datasets comprising ultrasound images and heart rate variability (HRV) data, with support vector machines (SVM) and bracket grounded on multiple association rules (CMAR) achieving notable delicacy situations.

Deep literacy, a subset of machine literacy, automatically identifies patterns and excerpts features from datasets, bypassing the need for homemade point selection. Convolutional neural networks (CNNs), a popular deep literacy system, have proven effective in image bracket tasks. Pretrained networks, similar as SqueezeNet and AlexNet, enable transfer literacy, easing point birth and bracket without retraining entire models.

This study proposes a feather light CNN armature for prognosticating cardiovascular conditions using 12- lead ECG images. The proposed model achieves a remarkable delicacy of 98.23, outperforming being models, including SqueezeNet and AlexNet. also, this work evaluates the transfer literacy capabilities of SqueezeNet and AlexNet as point extractors and integrates these features with conventional machine learning classifiers, similar as SVM, K- NN, DT, arbitrary timber(RF), and NB. The structure of this composition is as follows Section II provides a review of affiliated work, Section III outlines the styles and the proposed CNN model, Section IV describes the dataset and experimental setup, Section V discusses the results, and Section VI concludes with perceptivity and unborn exploration directions. Heart disease is the most serious challenge to health worldwide. The WHO states that every year, about 17.9 million people die from it-that's a third of the deaths in this world. A shocking number, no doubt, as about 85% of these are caused by myocardial infarctions, otherwise known as heart attacks. But there's hope: catching heart problems early can greatly lower the risk of death and improve the quality of life for millions.

Doctors have several tools to spot heart problems, including electrocardiograms (ECGs), echocardiograms, MRIs, CT scans, and blood tests. Among these, ECGs are one of the most common because they're quick, non-invasive, and affordable. An ECG records the heart's electrical signals, helping doctors detect irregularities. However, reading ECGs accurately takes time and expertise, and even skilled professionals can sometimes miss subtle warning signs.

This is where Artificial Intelligence makes a real difference. AI, especially through ML and DL, is transforming how we detect and manage heart diseases. These technologies can analyze ECG data much faster and more accurately than traditional methods, helping doctors diagnose conditions earlier and more reliably.

It is essentially teaching a computer to spot patterns in data, similar to how doctors spot signs of heart problems. Much of the time in ECG analysis involves the identification of feature extraction and selection, focusing on the most important parts of the data. Deep learning pushes this further: it allows the computer to automatically learn complex patterns from images of an ECG, without human input. Convolutional Neural Networks are a type of deep learning model that is very good at pattern recognition in images, which makes them very suitable for ECG analysis.

AI-powered ECG analysis can identify subtle, early signs of heart disease that might otherwise be missed during manual reviews. This technology supports doctors in making faster, more accurate diagnoses but also opens the door to continuous heart monitoring through wearable devices. As AI continues to advance, it holds incredible promise for improving how we detect and treat heart disease, ultimately saving more lives and offering people a healthier future.

Literature review

Machine learning (ML) and deep learning (DL) are increasingly used for predicting cardiovascular diseases (CVDs), utilizing ECG data in digital and image formats. Various studies have showcased the strengths of these approaches in improving accuracy and efficiency.

Bharti et al. [4] conducted a comparison of ML and DL methods on the UCI heart disease dataset. Their DL model, featuring three dense layers (128, 64, and 32 neurons with dropout rates of 0.2, 0.1, and none, respectively), achieved 94.2% accuracy. Traditional ML models, even when enhanced with feature selection, showed lower accuracy, with K-Nearest Neighbors (84.86%) and Logistic Regression (83.31%) outperforming Decision Trees (82.33%) and XGBoost (71.4%). The findings highlighted DL's ability to outperform ML in tasks requiring minimal manual feature engineering.

Kiranyaz et al. [7] proposed a one-dimensional convolutional neural network (CNN) to process extended ECG recordings. Their model, trained on the MIT-BIH dataset, accurately classified ventricular and supraventricular ectopic beats with success rates of 99% and 97.6%, respectively. Another CNN model with max-pooling layers, dense layers, and a softmax output achieved a classification accuracy of 92.7%.

Khan et al. [3] utilized transfer learning through the SSD-MobileNet-v2 model to classify ECG images into four categories: abnormal heartbeat, myocardial infarction (MI), history of MI, and normal cases. Their approach, which included data partitioning (80% training, 20% testing), resulted in a precision rate of 98.3% for MI detection. The training process spanned four days, demonstrating the robustness of transfer learning for medical applications.

Rahman et al. extended this concept to classify both COVID-19 and cardiac abnormalities using deep CNNs. Their experiments involved six pretrained models, such as ResNet and DenseNet, applied to a five-class dataset that included COVID-19 and various cardiac conditions. Preprocessing steps like gamma correction and z-score normalization were employed. DenseNet201 reached 99.1% accuracy for two-class classification (COVID-19 vs. normal), while Inception-V3 achieved 97.83% for all five classes.

Pal et al. [8] addressed arrhythmia classification using CardioNet, a CNN-based model leveraging transfer learning and DenseNet architecture. The PTB and MIT-BIH datasets, balanced with data augmentation techniques, were used for training. DenseNet's efficient gradient handling led to precision, recall, and F1 scores exceeding 98%, solidifying its effectiveness in identifying cardiac abnormalities.

Avanzato and Beritelli designed a CNN model with four 1-D convolutional layers, each followed by batch normalization, ReLU activation, and max-pooling. With additional average pooling and softmax layers, the model achieved 98.33% accuracy on the MIT-BIH dataset.

Acharya et al. implemented a CNN with four convolutional layers and three dense layers to detect myocardial infarctions from ECG signals. Their model used the leaky ReLU activation function and max-pooling, achieving 95.22% accuracy on noise-free data, a notable improvement over the 93.53% on noisy signals.

Naz et al. converted ECG signals into binary images for use with pretrained CNNs like AlexNet and Inception-V3. Features extracted via transfer learning were classified using SVM, achieving 97.6% accuracy in detecting ventricular arrhythmias.

Methods

Convolutional Neural Networks (CNNs)

CNNs are specialized deep learning models widely used in image-related tasks. They analyze data through layers organized in three dimensions: height, width, and depth (channels). For instance, an image with dimensions 227 × 227 × 3 refers to a width and height of 227 pixels and 3 color channels.

The convolutional layer applies filters over the input, producing feature maps that highlight patterns like edges or textures. Activation functions, such as ReLU, introduce nonlinearity, while pooling layers, like max-pooling, reduce feature map dimensions, making computations more efficient. At the end, fully connected layers and softmax functions enable prediction.

Pretrained Deep Learning Models

Pretrained models like SqueezeNet and AlexNet are effective for transfer learning and feature extraction, offering faster implementation and reduced training times. These models, trained on large datasets, can adapt to new tasks by replacing their final layers with ones tailored to specific objectives.

In transfer learning, the new layers are trained on a specialized dataset while earlier layers retain general features from the pretrained model. This allows for efficient use of limited resources and data. Extracted features can also train traditional classifiers like SVM or K-NN, bridging the gap between deep learning and conventional machine learning.

Proposed CNN Architecture

The proposed architecture includes 38 layers and employs a dual-branch structure to enhance feature extraction. It processes input images of 227 × 227 × 3 resolution.

Stack Branch

This branch features three convolutional layers with small filters (3 × 3), each followed by leaky ReLU, batch normalization, and max-pooling. These layers progressively extract detailed features, using increasing filter sizes (64, 128, and 224), and produce a feature map of 2 × 2 × 224.

Full Branch

This branch starts with a fully connected layer, followed by additional convolutional layers to capture more general patterns. Features from this branch create a 2 × 2 × 96 map, which merges with the stack branch output for comprehensive analysis.

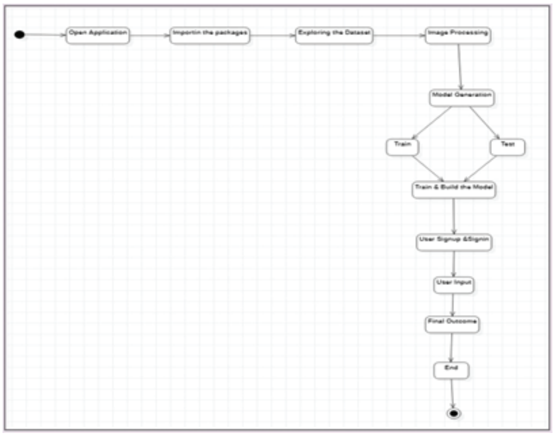

Figure 1. *Architecture of proposed CNN model.*

Output Layer:

A 1 × 1 convolutional layer reduces computational demands, followed by a fully connected layer with four outputs, representing classification categories: Normal (NP), Abnormal Heartbeat (AH), Myocardial Infarction (MI), and History of MI (H.MI). A softmax function determines the final prediction.

The model processes ECG images after they undergo cropping, resizing, and augmentation. Once trained, it achieves accurate categorization of ECG inputs into the specified classes.

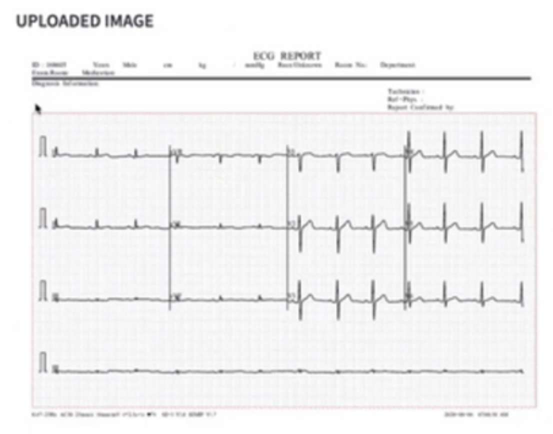

Figure 2. *ECG image dataset*

Experiments

The methodology, in this work, we analyze the applicability of the proposal using an available dataset related to ECG images of heart diseasesNP = Normal Person AH = Abnormal Heartbeat; MI = Myocardial Infarction; and H.MI = History of Myocardial Infarction. NP represents patients free of heart problems, AH are those with disturbed heart rhythms, MI is referring to patients suffering from heart attack, and H.MI denotes patients who recovered from heart attack. Samples of ECG pictures of these patients

To increase the robustness of the model and address class imbalance, we made use of data augmentation. In this approach, we rotated, flipped, and translated images. The result is that the number of images now increases to 4700 images. This improves the generalization ability of the model when it trains because of learning diverse features.

The experiments were conducted on a system that had MATLAB 2021b installed on it, with an Intel Core i7-4510U CPU, 8GB of RAM, a 4GB NVIDIA GeForce 820M GPU, and Windows 10 Pro 64-bit. Before training, preprocessing was performed on the ECG images to only include the necessary features for the analysis. The headers and footers of the images were cropped, as shown in Figure 5, because they were not required. The images were then resized to 227×227 pixels with three RGB channels. This standardized the input format to the neural network.

For the training process, we used Adam optimizer with a batch size of 128 and trained the model over 16 epochs. Each epoch involved 29 iterations, totaling 464 iterations for the entire training phase. We experimented with different learning rates to find the optimal configuration for the model. To ensure the results were reliable and generalizable, we performed fivefold cross-validation. The dataset was split into five parts, with four used for training and one for testing. This was replicated five times on different splits with results averaged out to give an overall assessment of the model performance.

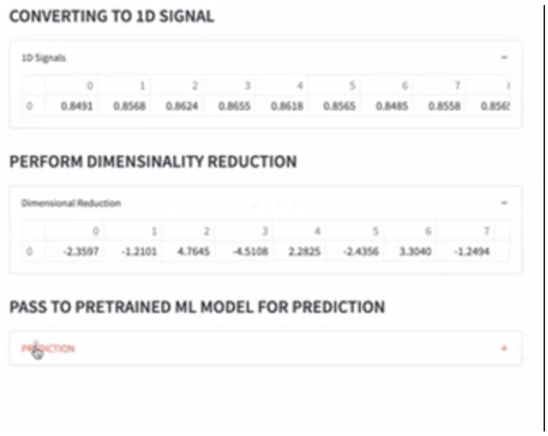

Figure 3. *Output*

Results and discussion

The models were tested for accuracy, precision, recall, F1 score, and training and testing time. All these are based on the confusion matrix. Recall gives the correctly identified positive cases in terms of all actual positive cases, and precision provides the ratio of the actual correct identifications of positive cases.

Transfer Learning and Proposed CNN Model Results

This experiment used transfer learning with pre-trained networks, SqueezeNet and AlexNet, pre-trained on 1000 categories of images. To fine-tune these networks to our ECG image dataset, their final layers were replaced. For AlexNet, the final fully connected layer was replaced by a new one with four neurons corresponding to our classes. SqueezeNet had its final convolutional layer replaced with a new one containing four 1×1 filters. Both networks were equipped with a new classification layer to produce outputs based on softmax probabilities. The properties of these networks and our proposed CNN presents the performance metrics for SqueezeNet, AlexNet, and our proposed CNN at different learning rates (0.01, 0.001, and 0.0001). The proposed CNN achieved the accuracy of 98.23% when the learning rate was 0.0001. The performance chart of the suggested model is given below that shows a consistency in high accuracy at all learning rates. SqueezeNet and AlexNet also performed pretty well at 0.0001 but quite poorly at the high learning rates. Therefore, preferring a lower learning rate to prevent local minima during transfer.

Our proposed CNN model outshines those models in terms of accuracy as well as computation efficiency. Though SqueezeNet has lesser number of parameters, its computation load in the convolution layers is too high. So the time taken to process the system goes higher in the case of the single CPU.

Figure 6: Training curve of proposed CNN on ECG dataset in fold-1 with a learning rate of 0.0001. Accuracy increases at each iteration and loss decreased smoothly to 0.0043. Confusion matrices for each fold after training the proposed CNN with a learning rate of 0.0001.

Khan et al. conducted the related study where the same data set was used that was divided in 80 % for training, and 20 % for the testing purpose using batch size = 24 with a learning rate = 0.0002, and their training of the model took around four days, whereas the precision rate for the class MI was up to 98.3 %; our proposed CNN outperformed this at a precision rate of 99.4% for the MI class.

Results of Pretrained Models Using for Feature Extraction

We used the pretrained networks SqueezeNet and AlexNet to take features from our ECG images and compared that with the proposed CNN model taken features. The deep learning offers the feature extraction without retraining the whole network. The features were obtained by propagating the input images through the network up to a particular layer: conv10 (layer 64) for SqueezeNet, fc7 (layer 20) for AlexNet, and fc02 for our proposed CNN at layer 32. These features were used to train the machine learning algorithms: SVM, K-NN, DT, RF, and NB.

Our performance metrics, based on the accuracy, recall, precision, and F1-score measures, show a maxi of 99.79% accuracy as obtained by NB using features of our proposed CNN. SVM got accuracy rates at the levels of 99.47%, 97.87%, and 97.66% with features obtained from our CNN, SqueezeNet, and AlexNet respectively. Overall, our proposed CNN gave the highest results in terms of all these performance measures.

In comparison, SqueezeNet compared with AlexNet gave better accuracy to SVM, RF, and NB algorithms but needed longer training and testing times since feature sizes were bigger. Though our CNN model had an extracted feature size much smaller, it still showed a better performance and thus effectively extracted the important features from the ECG dataset. Therefore, our model shows higher accuracy with lesser computational cost. Optimizing the hyperparameters could further enhance this model.

Conclusion

This research successfully demonstrates the efficacy of machine learning and deep learning techniques in detecting cardiovascular diseases using ECG images. By developing a novel lightweight CNN architecture, the study achieved an impressive accuracy of 98.23% for classifying four major cardiac conditions. When utilized as a feature extractor, this model further enhanced the performance of traditional machine learning algorithms, with the Naïve Bayes classifier attaining an unparalleled accuracy of 99.79%. The findings underscore the potential of integrating AI-driven solutions into healthcare systems for early and accurate disease detection. The proposed method is computationally efficient and capable of functioning on basic hardware setups, making it a viable candidate for inclusion in IoT healthcare ecosystems. Future research should explore the scalability of this model to larger datasets and its application to real-time monitoring systems for broader healthcare applications.

Future Scope

- **Future of Heart Health with AI:** A More Caring Approach With technology and innovations constantly moving forward, heart care is destined to get much better. From detecting heart disease in the early stages, to efficient treatment, even preventing it entirely, AI stands as the forerunner towards such a bright future. Here is what could potentially unfold:

That is your heart's personal watchdog, imaginable as a smartwatch that does not just count your steps but watches over your heart every single day. These future wearables will have the capability to detect even the smallest changes in your heartbeat and will notify not only you but also your doctor instantly. With such 24/7 monitoring, heart problems could be caught before they become serious, giving you even more control over your health.

- **Care That's All About You:** We're all different, and so are our hearts. With AI, doctors will be able to create treatment plans that are tailored just for you. This means more effective medications, fewer side effects, and a treatment experience that truly fits your needs.
- **Catching Issues before They Get Too Serious:** This is where the AI really kicks in, finding the smallest deviation in heart rhythm patterns that might evade the human eye. This potentially means we'd be warned even before the seriousness of the disease can cause the harm, meaning interventions could begin earlier and end lives.
- **Smarter Tools for Doctors:** The future of AI-powered diagnostic tools will be so accurate and user-friendly that doctors will rely on them like they rely on their own experience. This will enable doctors to identify problems faster and more accurately, and you will receive the right treatment at the right time.
- **Heart care wherever you are:** For many individuals living in rural areas, accessing heart specialists can be challenging. But with AI tools, this is no longer the case. These smart tools will make quality heart care more accessible and affordable, regardless of where you live.
- **Predicting Heart Health Early On:** What if you could know years in advance whether you were going to develop heart disease? If AI could process the tremendous health data we could predict potential problems before they show up, so we can help change habits before they develop heart disease.
- **A Complete Picture of Your Health:** AI could seamlessly connect with your health records, giving doctors a full picture of your medical history. This will lead to smarter decisions and better long-term care because your doctor will have all the information they need at their fingertips.

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