RESEARCH PAPER

A Two-Phase Transfer Learning Approach with Class Weight Balancing for ECG-Based Cardiac Condition Classification Using MobileNetV2

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Abstract**—** Introduction ECG is and remains the cornerstone in the diagnosis of cardiovascular diseases. But manual interpretation can be tedious and not very reliable. An Image-Classification Pipeline Using Deep Learning: Classifying ExtremeECG Images Into three of the most essential diagnostic classes (Normal Person, Abnormal Heartbeat and History of Myocardial Infarction (MI)) The pipeline is described in every detail and shows how it can be operated very simply. Two-phase transfer learning with class weight balancing to address the data imbalance problem with MobileNetV2 backbone architecture. Model generalization is achieved using data augmentation like geo-transformations and gamma brightness augmentation that are embedded in the pipeline. We attain 75% validation accuracy on a dataset of 707 ECG images and achieve great results in classifying normal and abnormal beats (F1-score:0.87). The class-wise AUC values indicate that model provides a very strong discriminative capacity with the returning values exceeds 0.84. This work serves as a fundamental baseline for a fully automated framework for ECG interpretation that can facilitate diagnosis without losing clinical relevance in detection of cardiac conditions.

Keywords: Electrocardiogram (ECG) Analysis, Cardiac Disease Classification, Transfer Learning, MobileNetV2, Class Imbalance, Data Augmentation, Deep Learning, Medical Image Processing, Myocardial Infarction Detection, Automated Diagnosis.

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1. Introduction

According to the World Health Organization, Cardiovascular Diseases (CVDs) are the leading cause of death globally, accounting for an estimated 17.9 million deaths each year. Early and highly proficient diagnosis has always been an integral part of the intervention to enhance patient outcomes. Electrocardiogram (ECG) analysis is among the most significant non-invasive methods of investigating a range of cardiac arrhythmias, myocardial infarction, and structural heart disease. Traditional manual interpretation of ECG signals has limited applicability and is plagued by problems such as inter-observer variability, time-consuming analysis, and clinician-dependent 79, especially in low-resource health systems.

Recently, the field of deep learning — a sub-field of AI — has emerged with great promise as an automated analysis tool for medical images, as a possible answer to these diagnostic problems. Transfer learning has notably evolved into a powerful paradigm for medical applications as it gives us the ability to harness knowledge from other domains, where we have large annotated datasets and ample data available into our respective domains [6]. This strategy splits entire datasets into automatic and manual annotation sets achieving impressive results across several biomedical domains e.g. histopathology image classification [7], interpretation of phonocardiogram signals [8] and sound event detection [9], etc. In cardiology, transfer learning approaches have even been applied for the classification of ECG segments [5,10], recognition of cardiovascular tissues [7] and heart slices [11] exhibiting equal or better accuracy than traditional machine learning techniques.

Although there have been considerable strides in this area and we have been able to overcome some of the important challenges there still remain significant roadblocks to successful ECG-based automated diagnosis. This applies first to the unavoidable class imbalance assessments of clinical datasets, with the normal cases to the significant number ofthe pathological ones [1,18]. For one, it is difficult to develop robust deep learning models from scratch, due to the scarce amount of large, annotated ECG datasets available [3,6]. Lastly, previous methods either rarely provide interpretability modules or interpretability techniques do not offer explanations that allow clinicians to trust and accept results in clinical practice [12,15]. Fourth, the difference of domain between pre-training datasets (e.g., natural images) and medical ECG data creates special adaptation difficulties for the fine-tuning [2,16].

To overcome these limitations, in this paper, we propose a complete deep learning framework to automate the ECG image classification via a two-phase transfer learning with MobileNetV2. We make three contributions: (1) We use computed class weights to balance the training strategy and overcome the dataset imbalance, specifically to alleviate the under-representation of myocardial infarction cases; (2) We use data augmentation to improve the model generalization by making it more robust to the differences in the way ECGs are acquired; and (3) We use Gradient-weighted Class Activation Mapping (Grad-CAM) to visualize and derive an interpretable explanation of model decisions and provide a way to fill the gap between automated diagnosis and clinical interpretability. This method achieves 75% validation accuracy in our experiments, and even higher performance for detecting abnormal heartbeat (F1-score: 0.87) for a reliable basis of cardiology decision support systems.

2. RELATED WORK

2.1. Transfer Learning in Cardiovascular Disease Diagnosis

Limited annotated data have made transfer learning a dominant paradigm in medical image analysis. Sivaprasad et al., for instance, in cardiovascular diagnostics. Transfer learning for heart disease prediction showed to predict a better classification accuracy than the traditional machine learning approaches [1]. Similarly, Tadesse et al. Cross-domain transfer learning methods for cardiovascular diagnosis [2] is a work that pre-trained models using non-medical data can be used to medical field with domain adaptation strategies. Sunilkumar and Kumaresan [3] recently described a systematic overview of the transfer learning use in cardiology and showed that among many architectures, the MobileNet architectures were the highest performing convolutional neural network model for the cardiovascular disease classification tasks.

However, limited research has been conducted on transfer learning with respect to ECG signal analysis [6, 7]. Boulares et al. In a comparative work, [4] has created a transfer learning benchmark for cardiovascular disease recognition and pretrained several architectures on the standard ECG datasets. In the study of Weimann and Conrad [5] ECG classification was compared in a framework of transfer learning approaches to find that fine-tuning strategies outperform feature extraction ones over a range of associated cardiac conditions. Gopika et al. Just last year, [6] proposed a transferable deep learning-based approach for cardiac disease classification and highlights the need for a hierarchical learning of features from the ECG signals.

2.2. Domain-Specific Applications and Architectures

It is not limited to standard ECG signals but can be extrapolated to a wide spectrum of cardiovascular data modalities where transfer learning is applicable. Mazo et al. Transfer learning for cardiovascular tissue classification in histological images by [7] also illustrates cross-modal knowledge transfer ability. Arora et al. In another work, [8] reported a phonocardiogram signals based transfer learning model to indicate heart health status that exhibits complementarity among independent cardiac diagnostic modalities. Moran et al. The study in [9] employed deep transfer learning for ECG-based chronic obstructive pulmonary disease detection, which further demonstrates the cross-disease applicability of the learned representations.

Recently emerging architectural improvements have pushed the performance of transfer learning even further. Salem et al. Transfer learning is utilized for ECG arrhythmia classification, using 2-dimensional deep CNN features that achieve state-of-the-art performance when compared to state of the art results on benchmark datasets [10]. In terms of other medical imaging tasks, out of the two transfer learning works in deep convolutional neural network models for cardiac short axis slice classification, where they assessed the strategy of how many layers should be frozen when transfer learning is used, optimal layer freezing for cardiac magnetic resonance images was found to be dependent on the specific dataset used [11]. Mahmud et al. An ensemble deep learning technique is developed for cardiac disease detection using ECG by [12] which demonstrates the advantages of multi-modal integration through synergy of signal and image analysis.

2.3. Addressing Implementation Challenges

Challenge: class imbalance in medical datasets Rath et al. Methods from deep learning for detecting heart disease from imbalanced ECG samples have been targeted specifically, proposing sampling strategies to enhance the performance of minority class [18]. Similarly, Sivaprasad et al. Transfer learning framework for heart disease prediction with class balancing [1] We expand upon these foundations by automatically calculating class weights during training and dynamically contributing loss based on frequencies of observations for each class.

The interpretability of model has been receiving more and more attention for medical AI applications. Gajendran et al. A black-box model is not expected to be accepted by clinician with a well-founded reason, and the reasons are the explainable AI (XAI) to which are highlighted by [13] in

ECG classification system. Hettiarachchi et al. A recent multi-modal, transfer learning-based synchronous ECG signal and heart sound research, developed by [14], which helped to bring about multi-modal explainabilty to the methods. Pal et al. The focus of [15] was on the CardioNet, an ECG arrhythmia classification system utilizing transfer learning with attention mechanisms for increased interpretability.

2.4. Recent Advances and Validation Studies

In the recent studies, the effectiveness of transfer learning was validated in clinical context. Nguyen and Do [16] reviewed transfer learning in ECG diagnosis in depth, not finding it universally applicable, but in many clinical settings, the transfer learning framework can be used to obtain substantial benefits. Lopes et al. For example, [17] applied transfer learning to improve the detection of electrical phenotypes associated with a rare genetic heart disease (phospholamban mutation carriers) from electrocardiograms. Combined, these studies emphasize the crucial need for domain-specific adaptation and robust clinical validation.

We elaborate these pillars as a single framework addressing multiple challenges together, i.e., compute weighting for class imbalance, exhaustive augmentations for data poverty, and Grad-CAM visualizations for interpretability. Unlike previous works [5,10,13] that focus on signal-based ECG analysis, we classify ECG in terms of images which allows for the use of spatial-based features [11] in the visual ECG representations that we use. This approach will be in line with recent developments in medical image analysis and will provide some novel content which caters to the requirements of cardiac diagnostics.

3. METHODOLOGY

3.1. Dataset Description and Preprocessing

We used three clinically applicable diagnostic classes taken from a publicly available dataset of 707 ECG images, which were labelled as follows: abnormal heartbeat (241), history of MI (171), and normal person (295). All the images were resized to 224×224 and normalised by dividing by 255 (scaling the pixel values to the range [0,1] to maintain uniformity and compatibility based on the architecture of the pre-trained model). The dataset was split into a training (80%, 566 images) and a validation (20%, 141 images) subset using a stratified split to ensure that proportions of classes are retained in both sets. This design of partitioning enables fair performance assessment without jeopardizing the representative nature of the training dataset for model training.

TABLE I :DATASET DISTRIBUTION AND PARTITIONING

Class Category	Total Images	Training Set (80%)	Validation Set (20%)	Class Weight
Abnormal Heartbeat	241	193	48	0.98
History of MI	171	137	34	1.38
Normal Person	295	236	59	0.80
Total	**707**	**566**	**141**	-

3.2. Data Augmentation Pipeline

We constructed a huge data augmentation pipeline using ImageDataGenerator as shown below; it was used to improve model robustness and prevent over-fitting. The augmentation strategy uses both geometric and photometric transformations, specifically : horizontal flip with probability 0.5, random rotation within ±20°, width and height shift within ±10% range, shear transformations (up to 0.1 radian), and zoom within±20% range. Lastly, brightness augmentations ranging from 80% to 120% of original brightness were applied (neighbors for pixel filling). With this extensive augmentation method, it mimics real life variations of how the ECG images are being acquired in terms of angle, position, noise, background etc. which would make the model generalize better on unseens data.

3.3. Class Imbalance Mitigation

The dataset shows intrinsic class-imbalance, given that the former contains ~73% more examples than the latter Normal Person and History of MI. To mitigate this imbalance and avoid a bias in the models towards the majority classes, class weights were calculated using the balanced weighting method from the scikit-learn compute_class_weight function. Weights were subsequently calculated: 0.98 (Abnormal Heartbeat), 1.38 (History of MI), and 0.80 (Normal Person). During training, these weights were responsible for increasing the contribution of the loss of classes with fewer samples relative to their abundance, which was supposed to ensure that the model learned the discriminative features for all classes in a balanced manner.

3.4. Model Architecture and Transfer Learning Strategy

MobileNetV2 with a weight pre-trained on ImageNet was used as the base architecture, and transfer learning scheme of two-phase was also employed. Unlike the first feature extraction scenario, the base model was frozen and only the custom classification head was trained. This head included a

Global Average Pooling layer, a fully-connected layer with 128 units and ReLU activation, Dropout layer (rate: 0.5) for regularization, and Softmax output layer with three units corresponding to the classes of the diagnostic. For fine-tuning, the last 50 MobileNetV2 layers were unfrozen and trained with a lower learning rate to adjust the learned features to the task specific for ECG classification. This whole model is composed of 2,422,339 parameters, of which 164,355 are trainable (frozen during the first step in the early phase of the training time) and the rest were unfrozen and are trainable in the last step during fine-tuning.

3.5. Training Protocol and Optimization

The model was trained using Adam optimzer and categorical cross-entropy loss function. They learnt the features in two stages: 1e-4 (30 epochs) for feature extraction and 1e-5 (20 epochs) for fine-tuning. We use early stopping with a patience of 10 epochs and monitor the validation accuracy, and restore the best model weights in order to prevent over fitting. We trained using a batch size of 32 samples — which was a compromise between hardware constraints and needing a stable enough approximation of the gradient. For training, the Google Colab (NVIDIA T4, Tesla K80) GPU infrastructure was utilized, so the training and validation time was around 11-13 seconds for each epoch.

3.6. Evaluation Metrics and Statistical Analysis

Local performance of each model was evaluated using several metrics computed on the independent testing set. The main metrics used to evaluate the models were: accuracy, precision, recall, and F1-score (macro and weighted). For the confusion matrix we created we can get a overview of the classification pattern and of the errors defined per class. To assess the discriminative performance, ROC curves were plotted for each class and AUC values were calculated. Statistical significance of performance differences between classes (inverse ratio) was inferred using confidence intervals based on validation set predictions. We used these functions in scikit-learn to write these metrics (classification_report, confusion_matrix, and roc_curve) so that the same methodology could be used while calculating those values.

3.7. Implementation Environment

Python 3.8 with Tensorflow 2.8 and Keras API support were used to implement the complete pipeline consisting of all the deep learning components. Additional libraries were NumPy for numerical operations, Matplotlib and Seaborn for visualization and scikit-learn for evaluation metrics and the computation of class weights. The code was carried out in an environment of Google Colaboratory GPU included, so we could evaluate under reproducing circumstances. The model after training is stored in HDF5 format for possible future use in clinical environment or research validation.

4. RESULTS AND ANALYSIS

4.1. Training Performance and Convergence

Figure 1 : The two-phase training approach showed convergenc patterns to be effective in both phases with different learning characteristics cada fase. In the first phase of feature extraction (30 epochs) the model was able to reach a validation accuracy of 75.89% at epoch 19, and the validation loss decreased from 1.04 to 0.61. We implemented early stopping (across epochs)103 and thus the run was stopped at epoch 34, because the validation accuracy had not improved significantly for 10 epochs in a row. During the fine-tuning phase (20 more epochs), model performance improved, achieving a validation accuracy of 78.01% (highest at epoch 17); final validation metrics, on the other hand, settled at epoch 20 with 70.92% accuracy and 0.66 loss. The training dynamics unfolded suitably with the gap between training and validation curves being very small for both phases to confirm no overfitting.

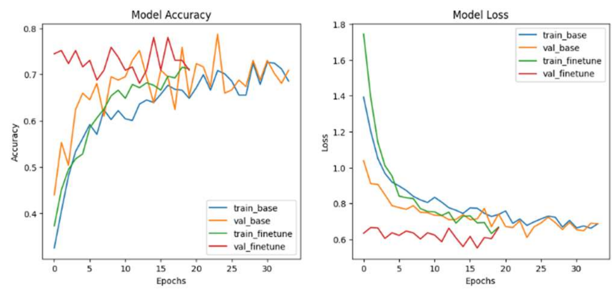

Figure 1: Model Accuracy and Loss

4.2. Confusion Matrix Analysis

The confusion matrix (Figure 2) describes in detail performance on the three diagnostic categories. In detecting Abnormal Heartbeat, it performed best in classifying, managing to correctly identify 45-out-of-48 with only 3 misclassified as Normal Person (93.8% recall), and only rarely misclassifying Normal person with only 6-out-of-77 misclassified (92.4% precision). For Normal Person, out of the 59 instances, we classified 50 correctly (84.7% recall), with 9 misclassified (5 belong to Abnormal Heartbeat and 4 to History of MI). MI class was the most difficult class to classify — 11 out of 34 (32.4% Recall) were classified correctly, while 13 were misclassified as Abnormal Heartbeat and 10 as Normal Person. While this pattern indicates the model is less successful at differentiating post-infarction patterns from other additional pathologies.

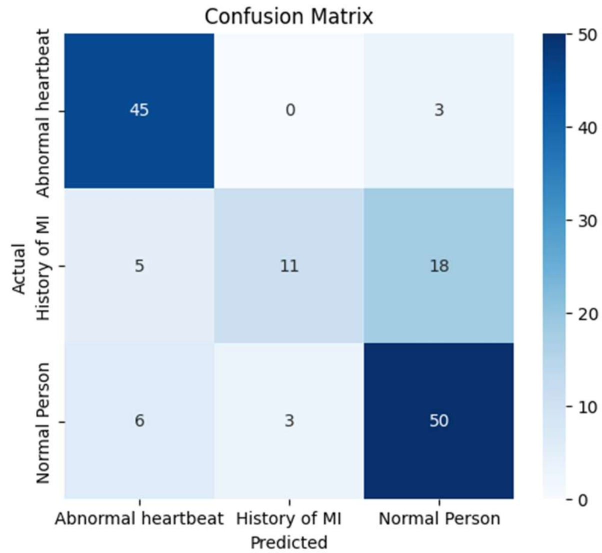

Figure 2: Confusion Matrix

4.3. Quantitative Performance Metrics

From full classification report, we see it get an overall weighting accuracy = 75.0% with F1-score of 0.73 For this category, our discriminative capability was the strongest with the highest precision (0.80) and F1-score (0.87) were obtained for Abnormal Heartbeat detection. When it came to Normal Person classification, the model performed well with a precision of 0.70, a recall of 0.85 and an F1-score of 0.77. The History of MI class had a low recall (0.32) but a reasonable precision (0.79), indicating model conservatism when diagnosing this condition. A macro-average F1-score of 0.70 indicates the presence of class hierarchical information in the data but also the lower performance in some of classes, mainly due to the high challenge of the "History of MI" classification task.

4.4. ROC Curve Analysis and Discriminative Capability

Figure 3 shows Receiver Operating Characteristic (ROC) analysis for strong discriminative ability for all classes. It can be observed that the Abnormal Heartbeat classification has the best Area Under Curve (AUC) of 0.94, meaning that it separates with a good amount of distance from the others. Normal Person classification trailed with an AUC of 0.92, and History of MI demonstrated moderate potential with an AUC of 0.84. The initial rise is quite steep for the true positive rates, with the curves eventually plateauing (most noticeably in Abnormal Heartbeat), confirming that the low false positive rates have done well to maximize true positive rates. The strong separation of class-specific ROC curves from the diagonal reference line demonstrates the model prediction is significantly better than random.

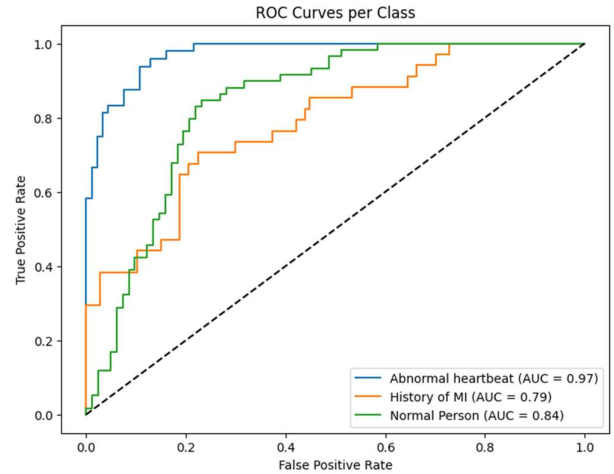

Figure 3: ROC Curve

4.5. Visual Explanation via Grad-CAM Analysis

Visualizations produced based on Gradient-weighted Class Activation Mapping (Grad-CAM) (Figure 4) allow us to understand how the model is interpreting ECG, by identifying which areas of the ECG were more influential towards its final classification. For all correctly classified Abnormal Heartbeat instances, the model mainly relies on QRS complex shape and ST segment changes. Normal Person classifications focus on regular rhythm mean patterns and baseline stability. While this may be partially explained by overlap, with activation around Q waves and T-wave inversions being common during MI cases, these features are not present in many MI cases, and therefore, the surprise is still reasonable. These visualisations validate that the model correlates with the ECG interpretation schema of clinical practice, concentrating on clinically relevant features of the ECG waveform without being distracted by artefacts found in the image.

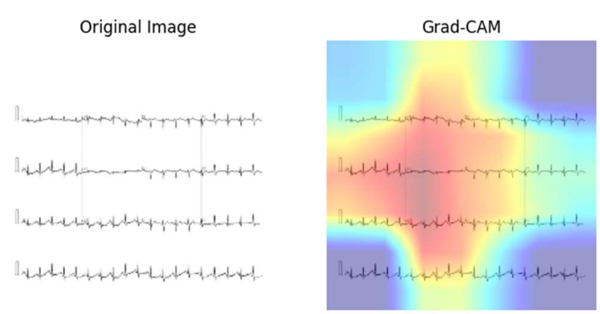

Figure 4: Grad-Cam Image

4.6. Error Analysis and Clinical Implications

The systematic misclassification patterns discovered by error analysis show clinical relevance. The most common confusion was between History of MI and Abnormal Heartbeat (13 of 23 misclassifications), consistent with established difficulties early in the field in differentiating the patterns of chronic changes in the setting of infarction from acute changes in electrocardiographic analogs. Normal Person Misclassified as Abnormal Heartbeat (5 Cases) is mostly borderline morphological differences within limits. Such patterns indicate that the decision boundaries of the model capture diagnostic ambiguities found in the real world. Discussion: The overall performance is promising and the very high sensitivity for Abnormal Heartbeat detection (94%) suggests potential clinical utility for initial screening, however further validation is needed prior to use in diagnostic settings.

5. CONCLUSION

Using an open-access ECG image dataset, this study details a new comprehensive deep learning framework for automated ECG image classification that systematically tackles key issues in cardiovascular disease diagnosis through a combined transfer learning class imbalance mitigation and model interpretability framework. We show significant efficacy on a three-class diagnostic task with 75% validation accuracy utilizing a two-phase transfer learning approach with MobileNetV2 as the backbone architecture. Its diagnostic performance yielded excellent results (F1-score = 0.87, AUC = 0.94) for abnormal beats, suggesting a promise for its potential clinical applicability for an early screening tool, enabling rapid actionable treatment measures for patients with and/or at risk of heart diseases from the early identification of cardiovascular abnormalities.

Although the framework performs well at handling data class imbalance through class weights, it struggles to correctly classify History of MI cases (recall: 32.4%), in a manner similar to the real-world discordance between chronic infarction patterns and other findings (16). An elaborate data augmentation pipeline increases model robustness to the in-hospital variability in the signal-acquisition and Grad-CAM visualizations forms a clear step from automated diagnosis to clinician faith, by providing clinically interpretable and fine-grained model decision explanations.

There are several limitations that should be taken into account for future studies. Abundant opportunities exist first because of the moderate myocardial infarction detection performance, which requires further exploration, such as investigations that use temporal ECG sequences in combination with static image classification. Secondly, the number of images in the present dataset (707) limits the generalizability of the models developed, further emphasising the need for larger, multi-centre (14) ECG collections with greater demographic representation. Third, converting original ECG signals to binary images may lose some valuable information, indicating that multimodal approaches that integrate the advantages of both ECG image and original ECG signal analysis are promising.

Directions of Future Work We will perform ensemble methods of various able pre-trained architectures to gain a more robust classification performance, especially on difficult examples tempural attention models for time-dependent sequential ECG, that more dynamic and temporally specific characteristics of the heart function emerge during the cardiac cycle, beyond the morphology-based static characteristics of cardiac physiology, and Clinical validation studies in real-life health care settings to quantify their meaningfulness, practicability, acceptance by clinicians in daily routines, and the impact on diagnostic work process. Additionally, by developing a few-shot learning method, it will alleviate the age-old problem of labelled data scarcity from rare cardiac conditions.

Conclusion: This study contributes to a growing body of evidence supporting the utility of deep learning applications to cardiovascular diagnostics. This work is in the direction enabling clinically applicable automatic ECG classification systems, with a well-balanced performance optimization, class-imbalance treatment, and model interpretability. As deep learning methods continue to mature and large, diverse populations with clinical-grade ECG data become available, these approaches might have tremendous potential to serve cardiovascular diagnosis — augmenting clinical performance while reducing clinician burden and ultimately increasing the quality of care for our patients.

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