AI novel Automated Heart Disease Classification & Prediction using Optical Flow with Deep Learning

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ABSTRACT

Heart disease generally refers to conditions such as heart failure, pain due to reduced blood flow to the heart (angina pectoris), or narrowing or blockage of blood vessels that can lead to stroke. Given the rapid increase in myocardial infarction among young people, I would like to establish a system to detect the symptoms of myocardial infarction at an early stage and prevent it from occurring. Because frequent, expensive tests such as medical records are not realistic for the average person, there is a need for a practical and reliable system for predicting the likelihood of cardiovascular disease. Therefore, we propose to develop an associate-grade application that can predict susceptibility to congenital cardiovascular disease based on basic symptoms such as age, sex, and pulse. Deep learning algorithms or models are used in planned plants because they have proven to be the most accurate and reliable formulas. This issue presents a deep learning technique in image classification to detect CHD anomalies using ResNet-50 architecture. The extraordinary power of deep learning classification has led scientists to use it in medical image processing. In this study, he trained ResNet-50 to image hearts with congenital heart disease. A model trained to distinguish between CHD and NOCHD ventricular septal defects. Three variants of test data (20%, 25%, and 40% of the full data set) were used to evaluate the prototype. Empirical results confirm that the application of ResNet-50 provides the most reliable performance in terms of precision, sensitivity, precision, and specificity values than ResNet-50 on three types of test data. After 3 sets of tests, we confirmed the best performance values on 20% and 25% test sets with >80% classification accuracy, >90% sensitivity, and >93% specificity. In this study, deep learning methods demonstrate reliable and reproducible results for biomedical image analysis.

KEYWORDS: *Deep Learning in medicine, Feature extraction and classification, tensorflow, keras, Data preprocessing, confusion matrix, opencv*

I.INTRODUCTION

Heart disease is the leading cause of death in the United States. According to the latest statistics from the American Heart Association, he has 121.5 million deaths from heart disease [1] in the United States. Identifying heart disease can be a difficult task requiring many biological indicators and risk factors in addition to age, gender, hypertension, diabetes, cholesterol levels, and many surrogate clinical indicators. I have. In many hospitals and clinics, follow-up patients [2] and detection of abnormalities and potential problems, such as extracting required drug events in pharmacovigilance [3], facilitate EHR-based public health surveillance [4]. We are considering an electronic health record (EHR) system. Establish and use the dynamic potential of handwriting methods to support early-stage [5] Parkinson's disease. Data mining has provided excellent solutions for many healthcare applications [6], medical image segmentation [7], patient deep representations [8], and computer-aided detection (CAD) tools for carcinoma diagnosing [9] associated interstitial lung disease such as: ILD) detection [10]. The complex nature of all medical datasets requires careful management, as one prediction error can have serious consequences. Therefore, clinical science disciplines have been rigorously employed to analyze EHR information and accurately classify disease-assisted machine learning algorithms and applied mathematical techniques. To this end, recent studies have used classification algorithms such as decision trees (DT) and Naive Bayes for predicting heart disease [11] and K-Nearest Neighbor (KNN) for automatic classification of blood pressure [12].In another study, his three different SVM classifiers was run to predict coronary artery disease [13]. An automated diagnostic system supporting heart sound [14] classification by support vector machines (SVMs) was commissioned to detect heart valve disease. In recent years, neural network models have shown excellent performance in tackling data prediction and various classification problems. Deep learning techniques have played an important role in healthcare for knowledge discovery and classification of diseases such as heart disease, diabetes, and brain diseases using biomedical data collected in [15,16]. We also mentioned the learning framework and some limitations and enhancement requests. In particular, many predictive model-based neural networks have been designed to accurately classify heart disease [17]. In a recent study, convolutional neural networks (CNNs) were implemented to identify heartbeats in different categories of ECG signals [18], and a modified deep convolutional neural network was used to combine ECG knowledge with conventional classified as abnormal [19]. Recurrent neural networks (RNNs) have also been used to predict future fatigue errors, model powerful patient representations in EHR [20], and temporal relationships between events in EHR knowledge [21]. Another study used the long short-term memory network (LSTM) to predict cardiovascular disease risk [22] and the gated recurrent unit (GRU) to predict vascular disease [23]. One of the biggest challenges in health analytics is the lack of collected EHR data to run correct predictive models. Large imbalances in the dataset distribution are another drawback for health analysis, especially heart disease classification.

This project presents automated cardiovascular disease classification and prediction that classifies different types of heart disease using optical flow based on deep learning models. The main purpose of this analysis is to improve prediction of performance accuracy in unbalanced cardiac disease.

II. LITERATURE SURVEY

Heart disease is a general term for any condition that makes the heart work and is indicated by chest pain or fatigue, an abnormal pulse rate, and many other symptoms. Diagnosis of heart disease has many risk factors. Some risk factors are related to age, gender and weight. Other risk factors are lifestyle-related such as smoking, hypertension, and alternative diseases such as diabetes and obesity. This multitude of factors makes it difficult for doctors to assess and diagnose types of heart disease. Artificial intelligence solutions are instructed to research and classify the EHR knowledge for heart disease prediction [24], by designing standard classification models such as support vector machine(SVM), a priori algorithm, decision trees, and hybrid random forest model [25,26].Heart failure prediction has been sculptural by looking forward to machine learning techniques applied to EHR data and reached a high AUC score of 77% using logistic regression with model selection supported Bayesian information criterion [27]. Moreover, machine learning techniques are verified to efficiently classify differing kinds of medical knowledge equivalent to magnet o-cardiograph recordings using k-nearest neighbor and XG Boost techniques [28], or clustering multi- label documents in order to help finding co-occurrence of cardiopathy with alternative diseases [29,30]. Advanced analysis in computing has induced accurate systems for medical applications and designed machine tools to extend the dependability of the predictive models whereas dealing with sensitive clinical data [31]. A new clinical prediction modeling algorithm has been developed to build heart failure survival prediction models and mostly applied to identify the complex patterns on EHR knowledge with various predictor–response relationships [32]. During this context, a deep learning approach was expeditiously enforced for medicine applications [33], and risk analysis of cardiovascular disease using an auto-encoder algorithmic program [34]. Another study directed multiple-kernel learning using an adaptive neurofuzzy inference system (MKL with ANFIS) for the diagnosis of heart disease and demonstrated high sensitivity (98%) and high sensitivity on the KEGG Metabolic Reaction Network dataset. A specificity (99%) was achieved [35]. A recent application required convolutional neural networks (CNNs) and multi-layer perceptrons (MLPs) for evaluation of fetal heart rate recordings, achieving 85% accuracy [36]. In addition to automatic detection of irregular beat rhythms in recordings with 83% accuracy, a recurrent neural network (RNN) was indicated. A long-term short-term memory (LSTM) network was used for transient fibrillation classification from various ECG signals, achieving an accuracy of 78% in and a score of 79% in [37]. In addition, a medical screening application for heart disease was solved using a CNN model for the task of automatically detecting the risk of cardiac structural abnormalities from digital electrocardiogram (PCG) signals [38]. Moreover, bifacial neural specification has been introduced for effectively up the accuracy of heart disease applications mistreatment the BiLSTM-Attention formula that reached higher results (accuracy of 99.49%) than the literature`s review [39].Other applications of deep learning bestowed in medical imaging and achieved the state-of-the-art results [40], and many challenging tasks were solved in biomedicine considering the utility of the neural networks [41]. A Generative Adversarial Network (GAN), which is composed of BiLSTM and CNN models, was suggested to address the problem of generating synthetic ECG data in order to boost the automatic medical-aided diagnosis and showed high morphological similarity to real ECG recordings [42]. Some other applications employed the Natural Language Processing (NLP) that helped to help doctors in heart sickness diagnosis, equivalent to suggesting comprehensive learning models from the electronic medical information mistreatment LTSM [43], and patient classes classification according to matter content using the attention based mostly BiLTSM model [44]. Data mining models are optimized by introducing new ideas like ensemble- learning models that improved the classification performance. This has been suggested by developing a prophetic ensemble-learning model on completely different datasets so as to diagnose and classify the presence and absence of coronary heart disease and achieved promising accuracy that exceeded the progressive results [45]. The concept of ensemble learning was further applied by aggregating the predictions of various classifiers instead of teaching private classifiers. An example of a related application was performed to predict coronary heart status using bagging trees and the AdaBoost algorithm [46]. Based on this, ensemble methods, mainly based on neural networks, were recommended to create additional effective classification models, and promising classification accuracies were shown in [47,48]. A relevant example of ensemble learning models has also been projected to heart disease detection using LSTM-CNN-based networks [49, 50]. There are many factors that can affect the performance of existing classification models applied to real data. One of these reasons is explained by the categorical imbalance in the training data set. The designed models were typically targeted to the majority of classes and made no attempt to generalize learning. Therefore, using proposed methods such as Smote [51], Edited Nearest Neighbors (ENN), and Tomek [52], we use information leveling was recommended.

III.PROPOSED MODEL

In this work, we adapted the learning process to transfer. ResNet-50 is a prebuilt model trained on the ImageNet dataset to identify individual images from 1,000 classes. The pretrained ImageNet weights served as initial weights for the proposed deep neural network. The remaining layers of ResNet50 play an important role in propagating large gradient values to previous neighboring layers. This layer allows the model to effectively extract complex and related patterns and solve the vanishing gradient problem. Our experimental setup leaves all levels of pre-training models open to discover new features in ultrasound imaging. Arrays captured from the CNN layer were delivered to a matching FC layer where a sigmoid function was used in the output layer. Additionally, Adam's optimizer was applied with his 0.00001 learning rate to improve accuracy. The loss function was set to binary cross entropy. A loss function indicates the difference between the actual value and the expected value. Set epoch to 80. The available data were highly imbalanced in sample numbers, so appropriate weights were assigned to each class to balance the data. See illustration. The full data set consists of a training data set containing 6327 images for training the model, a validation data set containing 790 images for fitting network parameters, and 792 images for evaluating model performance. The datasets were divided into various subsets, such as the test subset containing images. Data augmentation was also applied to produce a mirrored, zoomed, segmented, and scaled training data set, while the validation and test data sets were only scaled. Images were randomly selected from each category. The proposed architecture provides good results for predicting heart disease.

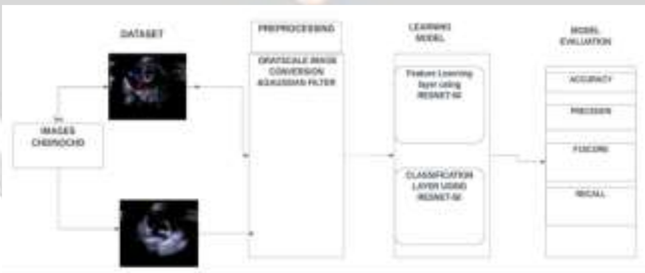

Figure: CHD Architecture Training

1. Collection of the dataset:

We have gathered CHD dataset from pedioecho.com website

2. Image augmentation:

Increase the sample size up to 10000 to do rotation and brightness techniques and change size and scale etc.

3. Assigning labels:

CHD has 1 and NOCHD has 0

4. Training pipeline:

Convolution neural network+Resnet 50

5. Model classification

Binary classification

6. Model evaluation: Confusion matrix
7. Metrics comparison:

a) Precision

b) Recall

c) Accuracy

d) Specify

IV.RESULTS

The results predicted an exemplary training accuracy of 99.70% and a validation accuracy of 99.24%. This determines the completeness of the version by the loss ratios obtained in training and validation of 0.190 and 0.0694 respectively. We found encouraging results with an accuracy of 99.24% and a cost of loss of 0.0491. In addition, confusion matrices and various evaluation parameters, as well as precision, recall and F1 scores were also carefully observed for deeper evaluation of the versions. We concluded that this efficiently classifies each pattern in data subsets with different versions.

CHD

NOCHD

V.CONCLUSION

The proposed model is superior to previous models and is sufficient to provide preliminary support to medical professionals for rapid and accurate decision making. Therefore, based on the off-the-shelf his Resnet50 architecture, a reliable and consistent CNN model using transfer learning techniques was developed.
In the future, this work will be extended to investigate one or more of his model parameters and their optimization. B. Network Complexity, Image Channels, Temporal Computation and Spatial Complexity. Additionally, a multiclass classification experiment is also performed on the same dataset.

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