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Automated Classification of Myocardial Infarction using Machine Learning approaches on ECG Images

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Abstract

Myocardial infarction, commonly known as a heart attack, remains a significant contributor to mortality worldwide. Timely detection and diagnosis are essential for effective treatment and improved patient survival rates. This study explores the application of machine learning algorithms for the automated classification of myocardial infarction using electrocardiogram (ECG) images. A comprehensive dataset comprising ECG images representing four distinct categories - Myocardial Infarction, Abnormal Heartbeat (Heart Arrhythmia), History of Myocardial Infarction, and Normal Cardiac Activity - was utilized for training and evaluation.

The dataset was divided into training and testing subsets to develop and validate machine learning models. Preprocessing techniques were applied to format the images, extract contour signals, and derive separate leads from each ECG image. The resulting 13-lead data was then converted into a CSV format, facilitating the application of machine learning algorithms. Various classifiers, including K-Nearest Neighbors (KNN), Random Forest, Support Vector Machines (SVM), and XGBoost, were employed for classification. Additionally, an ensemble model combining these algorithms was developed for improved performance.

Evaluation metrics such as accuracy, precision, recall, and F1-score were used to assess model performance. The proposed ensemble model, consisting of optimized SVM (SVM_C, SVM_gamma), KNN, and Random Forest classifiers, demonstrated superior results with an accuracy of 94.92%, a weighted average recall of 95%, precision of 95%, and an F1-score of 95%.

In conclusion, the findings highlight the effectiveness of machine learning techniques in diagnosing cardiovascular diseases through ECG signal analysis. The high accuracy and reliable performance suggest the potential for deploying these models in clinical settings to support early diagnosis and improve patient management.

Keywords: Electrocardiogram (ECG); Machine Learning; Ensemble Model; Myocardial Infarction; Cardiovascular Diseases (CVDs).

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1 Introduction

Heart disease remains the leading cause of death worldwide. According to the World Health Organization (WHO), cardiovascular diseases (CVDs) account for approximately 17.9 million deaths annually, representing 31% of all global deaths. Among these, 85% are due to heart attacks and strokes (WHO).

1.1 Impact of COVID-19 on Heart Health

A data analytics study conducted by Washington University highlighted the significant cardiovascular risks associated with COVID-19. The study found that individuals who contracted COVID-19 were:

- **72%** more likely to suffer from **coronary artery disease**
- **63%** more likely to have a **heart attack**
- **52%** more likely to experience a **stroke** Compared to those in the control group (*Health IT Analytics*).

1.2 Cardiovascular Disease in the United States

In the United States, CVD remains a significant public health concern. According to the Centers for Disease Control and Prevention (CDC):

- **1 in 4** Americans die of heart disease each year.
- Heart disease incurs an estimated **$363 billion** annually in healthcare services, medications, and productivity loss.

1.3 Risk Factors for Heart Disease

Common risk factors for heart disease include:

- High blood pressure
- High cholesterol
- Smoking
- Diabetes
- Obesity

Additionally, certain populations, particularly those of **South Asian descent**, are at a higher risk of developing CVDs.

1.4 Role of AI in Heart Disease Detection

Highly skilled clinicians can detect heart disease through electrocardiograms (ECG), which record the electrical activity of the heart. However, manual diagnosis can be prone to errors and is time-consuming ([5]). With advancements in Artificial Intelligence (AI), especially in Machine Learning (ML) and Deep Learning (DL), automated heart disease detection has shown promising results in reducing medical errors and expediting diagnosis.

A comparative study by M. Swathy and K. Saruladha highlights the effectiveness of machine learning and deep learning in classifying and predicting cardiovascular diseases (ICT Express, 2021).

1.5 Importance of Early Detection

Early detection and prevention are crucial in reducing mortality and disability caused by heart disease. Individuals can lower their risk by:

- Adopting a healthy diet
- Engaging in regular physical activity
- Quitting smoking

Furthermore, regular check-ups and ECG screenings enable early diagnosis, allowing timely and effective treatment.

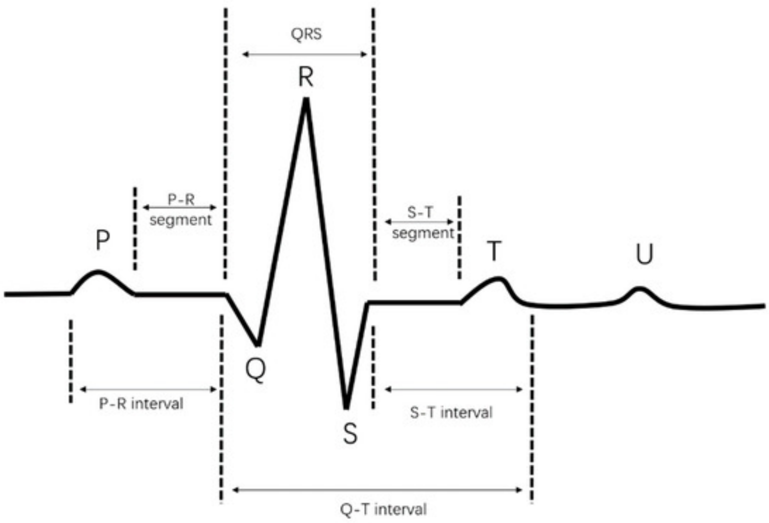
2 ECG Signal

An electrocardiogram (ECG or EKG) is a diagnostic test that records the electrical activity of the heart. It is widely used to diagnose and monitor various heart conditions, including heart attacks, arrhythmias, and heart failure. The procedure involves attaching electrodes to specific locations on the skin of the chest, arms, and legs. These electrodes capture the heart's electrical impulses and transmit the data to a machine that generates a visual representation, either on paper or a computer screen.

2.1 Components of an ECG Image

An ECG image consists of a series of waves and intervals representing different phases of the cardiac cycle. The primary components include:

- **P Wave**: Represents the electrical activity that triggers atrial contraction (depolarization). It is the first wave in the ECG cycle.
- **QRS Complex**: A series of sharp peaks and troughs that depict the electrical activity causing ventricular contraction. This phase is crucial for assessing ventricular function and identifying abnormalities.
- **T Wave**: Represents ventricular repolarization, indicating the heart's recovery phase after contraction.



2.2 Additional Measurements

ECG images also provide measurements that offer insights into the heart's rate, rhythm, and electrical conduction. These include:

- **Heart Rate**: Calculated from the intervals between QRS complexes.
- **Rhythm**: Evaluated by examining wave pattern regularity.
- **Abnormalities**: Irregularities such as arrhythmias or myocardial infarctions can be identified.

2.3 Types of ECG Monitoring

Beyond the conventional ECG performed in clinical settings, there are other forms of heart monitoring for continuous or long-term analysis:

- **Ambulatory ECG Monitors**: Portable devices used for continuous heart monitoring, usually for 24 hours or longer.
- **Holter Monitors**: Provide extended monitoring, capturing heart activity during daily routines.

2.4 Advantages of ECG

- **Non-Invasive and Painless**: Electrodes are simply placed on the skin.
- **Cost-Effective**: Affordable compared to other cardiac tests.
- **Diagnostic Accuracy**: Effectively detects various heart abnormalities.

Overall, ECG remains a fundamental tool in cardiology, providing critical information for timely diagnosis and management of heart diseases.

3 Related Work

Recent research has demonstrated that ECG signals can be effectively used for detecting myocardial infarction (MI) by identifying alterations in the signals. Numerous investigations ([24]-[27]) have been conducted to automatically predict cardiovascular diseases using machine learning and deep learning methodologies, leveraging ECG as image data for analysis.

In the study by [7], a deep learning approach was introduced to detect MI and its location using 12-lead ECG signals. The research identified ten geographical MI locations based on the presence of MI-related ECG perturbations: anterior (A), anterior lateral (AL), anterior septal (AS), inferior (I), inferior lateral (IL), inferior posterior (IP), inferior posterior lateral (IPL), lateral (L), posterior (P), and posterior lateral (PL).

Before feeding the data into the Convolutional Neural Network (CNN), the 12-lead ECG signals were digitized at a sampling rate of 1000 Hz. A wavelet transformation-based preprocessing method was applied to minimize noise and baseline wander. The preprocessed data was further segmented to detect the R-peak, which serves as a key marker for ECG analysis. The 10-layer CNN model produced ten numerical values for each 12-lead signal, indicating the possible MI locations. Lead 2 was predominantly used to localize MI within the body. While the CNN model demonstrated promising accuracy, its computational demands rendered it less practical for use in portable devices.

Another study [8] utilized ECG signals from 44 recordings within the MIT-BIH Arrhythmia Database to assess classification performance. ECG beats were labeled and categorized into five beat types in accordance with AAMI (Association for the Advancement of Medical Instrumentation) standards. A patient-specific small dataset was used for training purposes. The proposed CNN consisted of three 1D convolution layers, three max pooling layers, a fully connected layer, and a softmax layer. The first and second convolution layers used a filter size of 5, while a stride of 2 was applied to the initial two max pooling layers. This model achieved an accuracy of 92.7% in classifying ECG heartbeats.

Furthermore, the comparative study in [10] examined the performance of machine learning and deep learning methods using the UCI Heart Disease dataset for binary classification. The deep learning architecture incorporated three dense layers: the first layer had 128 neurons followed by a dropout layer with a rate of 0.2, the second layer had 64 neurons with a dropout rate of 0.1, and the final layer had 32 neurons. The deep learning approach achieved the highest accuracy rate of 94.2%. In contrast, machine learning models attained the following accuracy rates with cross-validation and hyperparameter tuning: Random Forest (RF) - 80.3%, Logistic Regression (LR) - 83.31%, K-Nearest Neighbors (K-NN) - 84.86%, Support Vector Machine (SVM) - 83.29%, and Decision Tree (DT) - 82.33%.

These studies highlight the significant potential of deep learning and machine learning models in the accurate diagnosis and classification of myocardial infarction using ECG signals.

4 Theoretical Background of Machine Learning

Machine learning is a subset of artificial intelligence that enables machines to learn from data without being explicitly programmed. The theoretical foundation of machine learning can be traced back to statistical learning theory and computer science.

Statistical learning theory provides the foundation for supervised learning algorithms. In supervised learning, an algorithm learns from a labelled dataset, where the inputs are labelled with their corresponding outputs. The goal of the algorithm is to learn a mapping function from the input to the output that generalizes well to unseen data. Statistical learning theory provides the framework for analysing the generalization performance of these algorithms.

In addition to supervised learning, there are also unsupervised learning algorithms that learn from unlabelled data. These algorithms typically cluster the data into groups or learn a low-dimensional representation of the data. The theoretical foundation for unsupervised learning is less well-developed than for supervised learning, but there has been significant progress in recent years.

Reinforcement learning is another important branch of machine learning that is concerned with learning optimal decision-making policies. In reinforcement learning, an agent interacts with an environment and learns to take actions that maximize a reward signal. The theoretical foundation for reinforcement learning is rooted in dynamic programming and control theory.

4.1 Categories of Machine Learning Techniques

4.1.1 Supervised Learning

Supervised learning involves learning from labelled data, where the inputs are labelled with their corresponding outputs. In other words, the algorithm is provided with a dataset where each example has a known output, and the goal is to learn a mapping function that can accurately predict the output for new, unseen inputs. Examples of supervised learning algorithms include linear regression, logistic regression, decision trees, random forests, and neural networks.

4.1.2 Unsupervised Learning

Unsupervised learning involves learning from unlabelled data, where the goal is to discover underlying patterns or structures in the data. The algorithm is not given any specific output to predict, and it must find its own structure in the data. Examples of unsupervised learning algorithms include clustering, dimensionality reduction, and anomaly detection.

4.1.3 Reinforcement Learning

Reinforcement learning is another category of machine learning technique that is concerned with learning optimal decision-making policies. It is a type of learning where an agent interacts with an environment and learns to take actions that maximize a reward signal. The goal is to learn a policy that maximizes the cumulative reward over time.

In reinforcement learning, the agent learns from trial-and-error experience by interacting with the environment. The environment provides feedback in the form of rewards or penalties to the agent for its actions. The agent's goal is to learn a policy that takes actions that maximize the expected cumulative reward.

Reinforcement learning can be applied to a wide range of problems, such as playing games, robot control, and autonomous driving. It has also been successfully applied to real-world problems such as recommendation systems, supply chain management, and energy management.

4.1.4 Ensembling

Ensembling is a technique in machine learning that involves combining the predictions of multiple models to achieve better accuracy and generalization. It is a powerful technique that has been widely used in various fields of machine learning, such as image recognition, natural language processing, and financial prediction.

Ensembling can be done in many different ways, such as bagging, boosting, and stacking. Each of these methods has its own advantages and disadvantages, and the choice of method depends on the specific problem and the type of models being used.

4.1.5 Bagging

Bagging, or bootstrap aggregating, is a method that involves training multiple models on different subsets of the training data. The idea is to create multiple diverse models that can capture different aspects of the data. Each model is trained independently, and the final prediction is obtained by averaging the predictions of all models. Bagging can reduce overfitting and improve the stability of the model.

4.1.6 Boosting

Boosting is a method that involves training multiple models sequentially, with each model trying to correct the errors of the previous model. The idea is to create a strong model by combining multiple weak models. Boosting can improve the accuracy and reduce bias of the model.

4.1.7 Stacking

Stacking is a method that involves combining multiple models by training a meta-model on the outputs of the base models. The idea is to create a model that can learn from the strengths and weaknesses of the base models. Stacking can improve the accuracy and generalization of the model.

Ensembling can be done using many different types of models, such as decision trees, neural networks, support vector machines, and regression models. The choice of models depends on the specific problem and the type of data being used.

Let Y be the target variable, X be the input features, and N be the number of base models.

The output of the ith base model for the jth instance is denoted as Mi(Xj), where i=1,2,...,N and j=1,2,...,m, where m is the number of instances in the training data.

The training set for the meta-model is denoted as (M1(X1), M2(X1), ..., MN(X1), Y1), (M1(X2), M2(X2), ..., MN(X2), Y2), ..., (M1(Xm), M2(Xm), ..., MN(Xm), Ym), where each instance consists of the outputs of all the base models and the target variable.

The meta-model is denoted as f(M1, M2, ..., MN), where f is a function that takes the outputs of the base models as input and produces the final prediction.

The goal of stacking ensembling is to learn the optimal parameters of the meta-model f that minimize the prediction error on the training set. This can be achieved by minimizing the following loss function:

$$L = \Sigma i{=}1m\ (Yi - f(M1(Xi), M2(Xi), ..., MN(Xi)))^2$$

where Σi=1m denotes the sum over all instances in the training set.

The optimal parameters of the meta-model f can be learned using various optimization techniques, such as gradient descent, stochastic gradient descent, or L-BFGS. Once the optimal parameters are learned, the meta-model can be used to make predictions on new instances by first passing the instances through the base models to obtain their outputs, and then passing the outputs to the meta-model to obtain the final prediction.

5 Methodology

5.1 Dataset

Accurately specifying the collection and gathering of data is a necessary and critical initial step. The ML methods were tested on the ECG Images dataset of cardiac patients [23]. This dataset contains 928 different patient records with four different classes: Normal person (NP), Abnormal Heartbeat (AH), Myocardial Infarction (MI), and History of Myocardial Infarction (H. MI).

The dataset contained ECG images of cardiac patients under the auspices of Ch. Pervaiz Elahi Institute of Cardiology Multan, Pakistan. The purpose of this organization is to foster the development of knowledge and research on cardiovascular diseases, as well as to support the scientific community's journey towards modern advancements. The dataset of cardiac patients was published on March 19, 2021 (version 2) by Mendeley Data, contributed by Ali Haider Khan and Muzammil Hussain [11]. The raw dataset of images can be directly downloaded from this link: https://data.mendeley.com/datasets/gwbz3fsgp8/2 .

Table 1 represents the description of each ECG category in terms of symptoms, influence on the human body, and the number of ECG images in each category. The number of leads for each category is defined by 12 leads.

Category	**Description**	**Images**
Myocardial Infarction (MI)	A heart attack, caused by the obstruction of blood flow to the heart muscle, leading to damage.	240
Abnormal Heartbeat	An arrhythmia, characterized by irregular or abnormal heart rhythms.	233
Previous History of MI (PMI)	Patients with a recent history of myocardial infarction in the recovery phase.	172
Normal	Individuals with no signs of cardiovascular abnormalities.	284

Table 5.1: Description of heart conditions with the number of images available

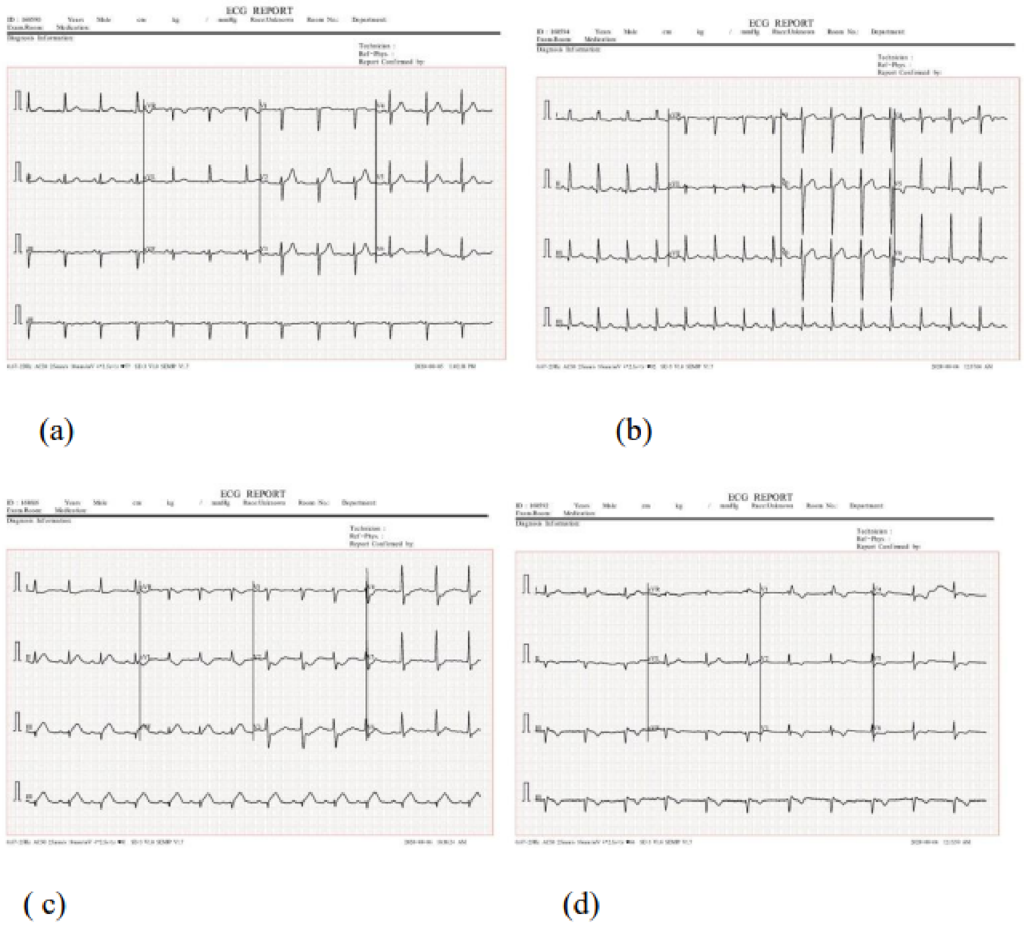


Fig: Samples from the ECG images dataset.
(a) Normal person. (b) Abnormal heartbeat.
(c) Myocardial infarction. (d) History of myocardial

5.2 Pre-processing

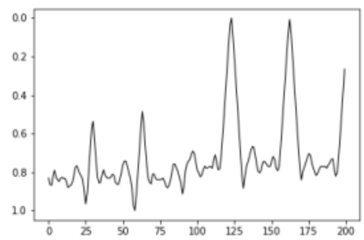
5.2.1 Conversion of ECG images into Gray Scale.

The primary objective of preprocessing is to convert raw data into a suitable format for further analysis. In this case, the preprocessing involves converting ECG images into grayscale. Typically, ECG images are acquired in RGB format with three color channels: red, green, and blue. Since color information is not necessary for ECG analysis, grayscale images using a single channel are sufficient. This reduces data dimensionality and simplifies analysis.

The preprocessing steps include:

- **Image Resizing**: Resize all ECG images to a uniform size for consistent analysis.
- **Color Space Conversion**: Convert RGB images to grayscale using the luminance formula.
- **Normalization**: Normalize pixel values to a standard range, enhancing analysis accuracy.
- **Image Enhancement**: Apply contrast stretching or histogram equalization to emphasize important features.

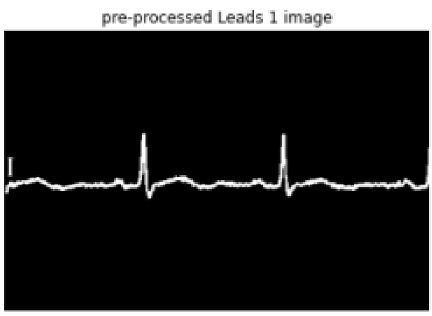
This standardized set of grayscale images serves as the input for subsequent machine learning algorithms



5.2.2 Conversion of Grayscale Images to Binary Images

After converting images to grayscale, the next step is converting them to binary images. This removes grid lines and separates the signal from the background for precise data extraction.

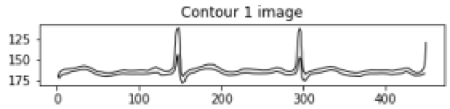
- **Thresholding**: Apply a threshold to convert images to black and white, simplifying further analysis.
- **Noise Reduction**: Additional noise reduction techniques are applied to improve signal clarity.



5.2.3 Conversion of Generated Leads into Contours

Each lead measures voltage differences across specific areas of the heart, providing a distinct view of its electrical activity. The contours extracted from these leads offer valuable insights into the heart's condition.

- **Signal Representation**: Convert ECG signals into a visual waveform using contours.
- **Lead Differentiation**: Each lead is represented distinctly to analyze heart functions from multiple perspectives.



5.2.4 Scaling and Normalization of Contours

Once the contours are generated, they are converted to one-dimensional signals representing the heart's electrical activity over time.

- **Signal Extraction**: Extract waveforms from images by sampling the ECG signal at regular intervals.
- **Normalization**: Apply MinMaxScaler to scale the signal between 0 and 1 for consistency across images and leads.

The normalized signal values for each lead (1-12) are saved in a CSV file, including a target label that indicates whether the heart is healthy or diseased. This labeled dataset supports supervised learning algorithms.

	0	1	2	3	4	5	6	7	8	9	...	191	192	193	194	195	196	197	198	199	target
0		0.888626	0.812245	0.665561	0.500157	0.39031	0.503157	0.671016	0.831373	0.930915	0.885081	...	0.403099	0.227493	0.071006	0.036642	0.182108	0.354795	0.526547	0.687533	2
1		0.807023	0.844462	0.858971	0.862217	0.849314	0.837517	0.832122	0.804881	0.745785	0.703045	...	0.706297	0.765693	0.784813	0.795663	0.809886	0.823817	0.811508	0.79958	2
2		0.653819	0.70996	0.754838	0.81714	0.915838	1	0.95502	0.839406	0.715041	0.594235	...	0.527485	0.653147	0.777326	0.86106	0.801774	0.72608	0.689121	0.644085	2
3		0.936459	0.936513	0.94311	0.941819	0.936485	0.936999	0.947314	0.923002	0.844092	0.757641	...	0.706292	0.800846	0.852939	0.859978	0.859977	0.854643	0.853353	0.859949	2
4		0.633524	0.711548	0.790842	0.857253	0.911213	0.939912	0.934426	0.894882	0.812718	0.706587	...	0.747938	0.84287	0.89864	0.907277	0.872172	0.810854	0.739755	0.65959	2
...		...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
487		0.899701	0.925065	0.953176	0.970737	0.97288	0.987581	0.999396	0.947425	0.817473	0.682324	...	0.715492	0.843744	0.931497	0.928955	0.914313	0.918867	0.894579	0.864759	3
488		0.882043	0.903099	0.954086	1	0.982167	0.943872	0.910847	0.907839	0.912979	0.901471	...	0.859483	0.852511	0.853891	0.883268	0.926698	0.945426	0.89719	0.851191	3
489		0.792318	0.805	0.787662	0.767232	0.802106	0.861793	0.868489	0.819355	0.766635	0.748084	...	0.726346	0.774266	0.825273	0.802655	0.740945	0.72379	0.751791	0.762488	3

5.2.5 Dimensionality Reduction using PCA

Principal Component Analysis (PCA) was applied to reduce the dimensionality of the extracted features while retaining maximum variance. The steps for applying PCA were as follows:

- **Centering the Data:** Subtract the mean from each feature to ensure the data is centered around the origin.
- **Computing the Covariance Matrix:** Calculate the covariance matrix to understand the relationship between features and assess correlations.
- **Eigenvalue Decomposition:** Perform eigenvalue decomposition on the covariance matrix to obtain eigenvectors and eigenvalues.
- **Selecting Top Eigenvectors:** Choose the top k eigenvectors corresponding to the largest eigenvalues to form the transformation matrix.
- **Projecting Data:** Project the original data onto the new coordinate system using the transformation matrix to reduce dimensionality.

The explained variance ratio was calculated to ensure the retention of most data information. This reduced feature set was then used for classification tasks.

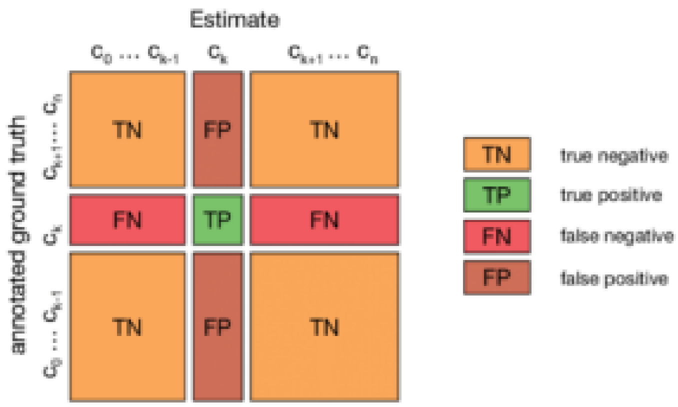
	0	1	2	3	4	5	6	7	8	9	target	
0		-0.549375	0.494565	-0.045338	1.422135	-0.268344	-1.590527	0.449342	0.875116	0.537622	-0.007312	2
1		-0.86306	-1.580209	0.514307	0.182243	-0.451672	-0.761466	-0.419687	-0.979922	-0.977254	-0.15015	2
2		-0.278309	0.626545	0.690094	-0.884929	-0.431733	1.087767	0.898435	0.482051	-0.000227	0.721407	2
3		-1.836973	-0.446914	1.372553	-0.256165	0.608453	0.087004	0.427743	-0.113751	0.104299	0.21023	2
4		-1.132701	-0.717709	0.090382	-1.262666	0.53316	0.439906	0.885697	0.572187	0.100195	-1.086943	2
...		...	...	...	...	...	...	...	...	...	...	...
487		-2.15717	-0.427223	0.292471	-1.614653	0.336949	-0.001895	0.78231	1.043056	-0.243457	-0.8456	3
488		-1.523648	-1.585517	0.4718	-1.570187	0.351871	0.258667	-0.013342	0.827453	0.109311	-0.819523	3
489		-0.200692	-0.29362	-1.00488	0.506783	1.626634	-0.473461	0.44773	0.041822	0.146146	0.037439	3
490		0.080288	0.438342	1.051315	0.642258	0.39241	-0.196922	0.539831	-0.720026	-0.312818	0.804052	3

6 Performance Matrices for Classification

The performance analysis of a model involves measuring various metrics such as Accuracy, Precision, Recall, F1 score, training and testing times. These measurements are typically based on the analysis of the data presented in a confusion matrix.

The definitions of these measurements are as follows:

- **Accuracy** refers to the percentage of correctly predicted observations relative to the total number of observations.
- **Recall** represents the ratio of correctly predicted positive observations to all positive observations in the true class.
- **Precision** expresses the ratio of correctly predicted positive observations to all positive predictions in the predicted class.
- The **F1 Score** is a weighted average of both Recall and Precision, taking into account both false negatives and false positives values.



In summary, these metrics are used to assess the effectiveness of a model in accurately predicting the target class. The accuracy, recall, and precision are all important measures of model performance, and the F1 score provides a comprehensive view of model performance by considering both false negatives and false positives.

7 Results / Conclusion

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
KNN Classifier	0.76	0.73	0.77	0.74
XG-Boost Classifier	0.90	0.91	0.90	0.90
Ensembled (SVM_Gamma, Random Forest, KNN)	0.93	0.94	0.94	0.93

Table 7.1: Performance comparison of different models.

According to the above models tested for the given approach, the best accuracy was achieved with an **Ensembled model** consisting of three different classifiers: Support Vector Machine Classifier, Random Forest Classifier, and k-Nearest Neighbour Classifier.

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