Fusion of Novel Leaf Morphometry Equations and Multiview Learning to enhance the Plant Leaf Classification

A Project-III submitted to the Mahatma Gandhi Central University

In partial fulfilment of the requirements

for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE & ENGINEERING

BY

AAKASH HARSH

DEPARTMENT OF COMPUTER SCIENCE AND INFORMATION TECHNOLOGY

MAHATMA GANDHI CENTRAL UNIVERSITY, MOTIHARI

BIHAR-845401, INDIA

JULY - 2024

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(MGCU2020CSIT3003)

Under the Supervision of

Dr. Vipin Kumar

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कंप्यूटर विज्ञान और सूचना प्रौद्योगिकी विभाग
Department of Computer Science and Information Technology
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DECLARATION

This is to certify that the dissertation entitled **"Fusion of Novel Leaf Morphometry Equations and Multiview Learning to enhance the Plant Leaf Classification"** is being submitted to the **Department of Computer Science and Information Technology, Mahatma Gandhi Central University, Motihari, Bihar - 845401, India,** in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology** in **Computer Science & Engineering**, is a record of bonafide work carried out by me under the supervision of **"Dr. Vipin Kumar"**.

The matter embodied in the dissertation has not been submitted in part or full to any University or Institution for the award of any other degree or diploma.

During the preparation of this work, I have not used any AI-based tool to write any part of this dissertation report. I take full responsibility for the submitted content including similarity.

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CERTIFICATE

This is to certify that this project entitled **"Fusion of Novel Leaf Morphometry Equations and Multiview Learning to enhance the Plant Leaf Classification"** submitted by Aakash Harsh**,** to the Department of Computer Science & Information Technology, Mahatma Gandhi Central University, Motihari, Bihar - 845401, India, for the award of the degree of **Bachelor of Technology** in **Computer Science & Engineering**, is a project work carried out by him under the supervision of **Dr. Vipin Kumar.**

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Acknowledgement

"Gratitude is not a thing of expression; it is more a matter of feeling."

There is always a sense of gratitude that one expresses towards others for their help and supervision in achieving goals. This B.Tech. project/dissertation is the result of a challenging journey, upon which many people have contributed and given their support. This formal piece of acknowledgement is an attempt to express the feeling of gratitude toward the people who helped me in successfully completing my Project. I would like to express my deep gratitude to Dr. Vipin Kumar, my supervisor for his constant support, supervision, guidance, and cooperation. He was always there with his competent guidance and valuable suggestions throughout the project. A special thanks to our hon'ble Vice Chancellor Mr. Sanjay Srivastava, my academic Dean Prof. Ranjeet Kumar Choudhary, Head of the department Dr. Vikas Pareek, and all the professors of my department for their support. I would also like to express appreciation to all the friends whose response and coordination were of utmost importance for the project. Above all, no words can express my feelings to my parents, classmates, and all those persons who supported me during my project. I am also thankful to all the respondents whose cooperation and support have helped me a lot in collecting the necessary information.

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Abstract

A plant species can be recognized by its flowers, seeds, and leaves as well as its physical aspects like maximum height, flower color, length of leaves etc. In recent years, the intersection of machine learning and botany has led to significant advancements in plant species identification and classification. This research paper delves into the realm of leaf image classification by deriving a novel feature extraction technique based on leaf morphometry equations and then deploying Multiview technique on views corresponding to different degree of equations.

The models used for classification are LR, KNN, SVM, DT and GNB. A total of 3 views are constructed corresponding to coefficients of leaf morphometry equations of degree 2, 3 and 4. After this, Early Fusion technique is used to create a Multiview architecture. A novel feature extraction method based on leaf morphometry equations has been performed to extract multiple views corresponding to different degrees of the equation. Various machine learning models are trained on each view and accuracy is recorded. A Multi-view model is built based on early fusion and its accuracy is compared with other individual views as well as the trivial method. For Flavia dataset, Multiview has achieved accuracy of 100% and hence surpasses the trivial method because trivial has scored only 78% in GNB. For MEW 2014 dataset, Multiview has not performed better than trivial method but is definitely better than each individual degree in most of the cases. MEW 2012 showed a surprising result where degree-2 has 100% accuracy in all the cases.

Future objectives of this project includes (but not limited to): To generate more views by extracting features from higher degrees, To find the best combination of views from the multiple set of views possible, Generalize the approach by validating it against more datasets.

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1. INTRODUCTION

As we all know plants are very essential parts of the biological ecosystem. Approximately 369,000 (94%) of the approximately 391,000 species of plants that are now known to science are blooming plants. In India, 45,000 plant species are recorded. A plant species can be recognised by its flowers, seeds, and leaves as well as its physical aspects like maximum height, flower colour, length of leaves etc. In recent years, the intersection of machine learning and botany has led to significant advancements in plant species identification and classification. Among various plant parts, leaves stand out as a rich source of information due to their diverse morphological features. Leveraging the power of machine learning algorithms, researchers have embarked on a journey to automate leaf classification, enabling swift and accurate identification of plant species.

This research paper delves into the realm of leaf image classification by deriving a novel feature extraction technique based on leaf morphometry equations and then deploying Multi-view technique on views corresponding to different degree of equations. As the demand for automated plant identification systems grows, the development of robust algorithms capable of accurately classifying leaves becomes imperative. Such systems not only aid botanists in their taxonomical studies but also find application in ecological monitoring, agriculture, and biodiversity conservation. The complexity of leaf morphology, influenced by various factors including species, environmental conditions, and genetic variations, presents a formidable challenge for traditional classification methods. However, the advent of machine learning has revolutionized the field by enabling the extraction of intricate patterns and features from leaf images.

This paper provides a comprehensive review of the methodologies, challenges, and advancements in leaf image classification through machine learning. Furthermore, we address the challenges associated with dataset acquisition, annotation, and preprocessing, which are pivotal in training reliable classification models. Moreover, we highlight the significance of interpretability and explainability in machine learning models, particularly in the context of botanical research, where insights into classification decisions are crucial for validation and further exploration.

In addition to technological advancements, it's essential to acknowledge the broader context of plant life and its significance to humanity. Plants not only provide oxygen, food, and medicine but also play crucial roles in ecosystems, climate regulation, and soil fertility.

However, human activities such as deforestation, habitat destruction, and overexploitation are threatening plant biodiversity worldwide. The exploitation of plants for commercial purposes, including agriculture, pharmaceuticals, and cosmetics, further underscores the need for efficient plant identification and monitoring systems. By accurately classifying leaf images, machine learning algorithms can aid in the identification of rare and endangered plant species, facilitate sustainable land management practices, and combat the illegal trafficking of endangered flora.

The aim of this paper is to provide researchers and practitioners with a comprehensive understanding of the current landscape of leaf image classification using machine learning techniques. By elucidating the methodologies and advancements in this domain, we hope to inspire further research and innovation, ultimately contributing to the development of more accurate and efficient automated plant identification systems, while fostering greater awareness of the importance of plant conservation and sustainable utilization.

2. LITERATURE REVIEW

The literature review has been done on the following two topics

1. Leaf Image Classification
2. Multi-view learning

2.1. LEAF IMAGE CLASSIFICATION

The paper by Novianti Puspitasari et al. (2023) aims to classify betel leaf species using four machine learning classifiers: Artificial Neural Network (ANN), k-nearest-neighbours (kNN), Naïve Bayes and Support Vector Machine (SVM). The evaluation in this research study deployed k-fold cross-validation with the value of k=5. The best performing classifier using colour and texture features was SVM with an accuracy score of 100%. The study comprised of following processes: Image Acquisition, Region of Interest (ROI) detection, Preprocessing, Feature Extraction and classification. The limitation of this research paper is that it focused on classification using colour and texture features only and did not explore any other options [1]. The work done by Chitranjan Kumar and Vipin Kumar used 25 classes of vegetable leaf image samples having 7226 RGB images. Various machine learning models were utilised like Decision Tree (DT), Linear Regression (LR), SVM, Multilayer Perceptron (MLP) and Naïve Bayes (NB). MLP classifier outclassed all other classifiers with an accuracy score of 90.68%. One major noticeable limitation of this paper is that it lacked diversity in image samples which can limit the generalizability of the model to real-world applications [7].

CNN emerged as the top performer in the investigation conducted by Eugene Val D. Mangaoang and Jaime M. Samaniego. The acquisition of leaf images through a scanner was a pivotal aspect of this research endeavour, contributing significantly to the management of image quality. Subsequently, the image dataset underwent duplication, resulting in two distinct sets. One of these sets underwent labelling according to their respective classes, preprocessing, and segmentation to facilitate feature extraction. Diverse leaf characteristics such as shape, colour, and texture were extracted during this phase. Following this process, machine learning algorithms including KNN, SVM, and BP networks were employed for training purposes, leading to the execution of classification tasks. In contrast, the other set remained unlabeled, designated for training and classification tasks specifically handled by CNN. The research findings indicated that leveraging all three leaf attributes for classification through BP networks yielded an accuracy rate of 93.48%, achieved through supervised learning techniques. Nevertheless, the most effective performer was identified as CNN, boasting an impressive accuracy rate of 98.5%. A notable limitation of this study pertains to the absence of comparative analysis between the proposed methodology and alternative approaches or algorithms utilized in the realm of leaf image classification [2].

In the study conducted by Aditya P. Bakshi and Vijaya K. Shandilya, saliency maps were utilized for background elimination, followed by their integration with a combination of various Fuzzy C Means (FCM) segmentation methodologies. These methodologies encompassed enhanced FCM, k-FCM, and original FCM, generating three distinct sets of images. Each of these image sets underwent individual processing to detect foreground pixels in green and yellow hues. The resultant image mask was then completed to enhance segmentation, after which the image sets were subjected to feature extraction. To effectively depict the images, a series of Colour, Texture & Convolutional feature maps were derived, aiding in the recognition of multidomain feature collections. These characteristics were classified using a blend of NB, MLP, Logistic Regression (LR), SVM classification techniques, thereby improving the effectiveness of disease detection across different types of crop. This combination allowed the suggested model to achieve a 3.5% improvement in classification accuracy, a 1.8% increase in response time, a 4.9% boost in precision, and a 5.5% enhancement in recall compared to current models. One aspect where this research paper lacked depth was the omission of details regarding the computational intricacy or resource prerequisites of the proposed model [3]. Preprocessing techniques like image re-orientation, cropping and greyscale conversion were used by Khaled Suwais et al. The paper focuses on the recognition of plants through their leaves, including the use of texture, shape and colour features. The research concluded that SVM and CNN are the dominant methods. However, the paper does not explicitly mention the limitations of the classification methods. [4]

Table 2.1. Works on leaf image classification

REF NO.	AUTHOR	YEAR	SUMMARY	CONCLUSION/ RESULTS	METHODS/ MODELS	LIMITATIONS
[1]	Novianti Puspitasari et al.	2023	The study aims to classify betel leaf species using a machine learning approach, combining colour and texture features and applying four classifiers.	SVM achieved the highest accuracy of 100%. Almost 99% accuracy was achieved in ANN, KNN and Naïve Bayes	KNN, Naïve Bayes, ANN and SVM	The study focused on the classification using colour and texture features but did not explore other potential features.
[7]	Chitranjan Kumar et al.	2023	The paper discusses the classification of vegetable plant leaf images using traditional machine learning models.	MLP algorithm outperformed others with an accuracy of 90.68%	Decision Tree, SVM, KNN, Linear Regression and Naïve Bayes.	Lack of diversity in image samples can limit the generalizability of the models to real-world scenarios.
[2]	Eugene Val D. Mangaoang et al.	2023	The paper discusses the classification of tree leaf species using different techniques of feature extraction and classification models.	BP networks achieved 93.48% accuracy in leaf classification and CNN achieved 98.5% accuracy for the same.	KNN, SVM, BP Networks and CNN classification algorithms.	The study does not compare the performance of the proposed approach with other existing methods or algorithms for leaf based classification.
[3]	Aditya P. Bakshi et al.	2022	The paper proposes a high-efficiency leaf image segmentation and classification model using an ensemble compute process.	3.5% better classification accuracy and 1.8% better response time	Naïve Bayes Multilayer Perceptron, SVM, Logistic Regression.	The paper does not mention the computational complexity or resource requirements of the proposed model.

[4]	Khaled Suwais et al.	2022	The paper focuses on the recognition of plants through their leaves, including the use of texture, shape and colour features.	SVM and CNN are the dominant methods.	Preprocessing includes Image re-orientation, cropping, and greyscale conversion.	The paper does not explicitly mention the limitations of the classification methods.

2.2. MULTI-VIEW LEARNING

In order to execute local feature and label selection for Multi-view multilabel classification, Jianhong Ma and Huiye Sun [8] suggested a unique group-based model that permits each view to have its own importance for grouping and each group to have its own associated labels model. They focused on the possibility that several views in multi-view learning could contain distracting and noisy elements. While several works aim at multi-view feature selection, the majority of them just carry out global feature selection, meaning that the feature selection weights are the same for all samples. Furthermore, a common assumption in multilabel learning research is that every sample has the same label correlation. Local patterns in the data, such as feature selection weights and label correlations that are shared locally by samples, may nevertheless be present. Both the assumption of shared label correlation in multilabel learning and the problem of noisy and irrelevant features in Multi-view learning are successfully addressed by the suggested group-based paradigm.

Qi Hao et al. [5] introduced a novel approach to multi-view learning through the utilization of the sub-view mechanism. The ease of implementation and the efficient utilization of latent features in multi-view data characterize this innovative method. The Multi-view learning process incorporates the PSVM-2V and MCPK models. This study outlines the construction of two sub-view learning frameworks, namely SL-PSVM-2V and SL-MCPK. The findings indicate that the proposed model enhances classification accuracy by approximately 1.91% compared to the original approach, showcasing superior anti-noise capabilities. However, the framework is limited in its consideration of a solitary view that contains privileged information, neglecting the potential presence of multiple views housing such valuable data.

A Multi-view structural large-margin classifier was proposed by Jie Zhao and Yitian Xu. [9]. Using a structural regularization term, it integrated consensus and complementary principles in all viewpoints to encourage separability between the class and each opinion as well as cohesion within the class. It addressed the issue that many current algorithms use pairwise approaches to handle multi-view problems, which severely limits the investigation of links between various perspectives and raises computing costs. This research study has two main features: (i) MvSLMC uses a structural regularization term to encourage separability between classes and cohesiveness within classes in each view. (ii) Various points of view benefit from each other's additional structural information, which increases the classifier's variety. It may not always be the case in practice, but the suggested approach assumes that each instance is represented by numerous distinct feature sets.

Huy Phan et al. [6] suggested a multi-view learning strategy for audio and music classification. A Multi-view embedding for classification is generated here by combining four low-level representations. In three separate classification tasks, the proposed Multi-view framework performs better than single-view baselines and existing Multi-view baselines based on concatenation and late fusion. In order to accomplish Multi-view embedding for classification, the proposed Multi-view network is composed of four sub-networks, each of which handles a single input type. Learned embeddings are concatenated. The lack of a thorough comparison with other cutting-edge approaches in the field of audio and music classification in this research makes it more difficult to assess how well the suggested strategy performs in comparison to other strategies already in use.

Stephanie Hormon et al. [10] proposed a multi-view framework for classifying high-risk morphology architectures in prostate cancer histopathology, which does not rely on ensemble techniques of single magnification models. The methods used in the paper are Patch based classification using different colourspace models and Multi-view framework for histomorphologic classification. The Multi-view framework achieved similar performance as individual magnification models. Also, the framework reduced computational complexity as compared to ensemble-based models. This framework utilizes a naïve implementation of multi-view images and may not fully exploit the potential benefits of ensemble-based techniques.

Table 2.2. Works on Multi-view Learning

REF NO.	AUTHOR	YEAR	SUMMARY	CONCLUSION / RESULTS	METHODS/ MODELS	LIMITATIONS
[8]	Qi Hao et al.	2022	The sub-view mechanism is used to offer a new multi-view learning technique. This innovative approach can efficiently leverage the hidden features in multi-view data and is simple to implement.	Proposed model improves classification accuracy by about 1.91% on the original basis. New method has better anti-noise ability.	PSVM-2V and MCPK models are used for Multi-view learning. Two sub-view learning structures SL-PSVM-2V and SL-MCPK, are constructed	Proposed framework only considers a single view containing privileged information and doesn't take into account the possibility of multiple views containing such information.
[5]	Jianhong Ma et al.	2023	The paper proposes a novel group-based model allowing each view to have its own importance for grouping and each group to have its own related labels model for Multi-view multilabel classification, which performs local feature and label selection.	The proposed group-based model effectively addresses the issue of noisy and irrelevant features in Multi-view learning, as well as the assumption of shared label correlation in multilabel learning.	The provided sources do not explicitly mention the proposed model for Multi-view multilabel classification	The paper focuses on Multi-view multilabel classification in the context of image benchmarks, limiting the generalizability of the models to other domains or datasets
[9]	Jie Zhao et al.	2023	Suggested a Multi-view structural big margin classifier that uses a structural regularization term to improve separability	The effectiveness of the proposed MvSLMC and its safe acceleration method is demonstrated through numerical	Multi-view Structural large margin classifier (MvSLMC). Introduction of Hinge Loss to construct a safe screening rule for	The proposed method assumes that each instance is represented by multiple different feature sets, which may not always be the case in

			between each view and the class and to integrate consensus and complimentary principles in all views.	experimental results.	accelerating the classifier.	practical scenarios.
[6]	Huy Phan et al.	2021	The paper proposes a multi-view learning approach for audio and music classification where four low-level representations are used to form a Multi-view embedding for classification.	The proposed Multi-view framework outperforms single view baselines and other Multi-view baselines based on concatenation and late fusion in three different classification tasks.	The proposed Multi-view network consists of four sub-networks, each handling one input type, and learned embeddings are concatenated to perform Multi-view embedding for classification.	The paper does not provide a detailed comparison with the other methods in the field of audio and music classification, which limits the understanding of the proposed approach's performance in relation to existing techniques.
[10]	Stephanie Hormon et al.	2020	The paper proposes a multi-view framework for classifying high risk morphology architectures in prostate cancer histopathology, which does not rely on ensemble techniques of single magnification models.	The Multi-view framework achieves similar performance as individual magnification models. The framework reduces computational as compared to ensemble-based models.	Patch based classification using different colourspace models. Multi-view framework for histomorphologic classification.	The framework utilizes a naïve implementation of multi-view images and may not fully exploit the potential benefits of ensemble-based techniques.

3. PROBLEM DEFINITION AND RESEARCH OBJECTIVE

3.1. PROBLEM DEFINITION:

The hand-crafted feature extraction method may not be very useful for effective learning of the model. The learning complexity has increased with variations present in different species. Therefore, the extraction of effective features is required to extract the discriminative and robust representation from the leaf images to enhance the leaf image classification using machine learning model.

3.2. RESEARCH OBJECTIVES:

The research objectives are as follows:

1. Collection of the plant leaf images of various categories i.e., available online and offline.
2. Identifying the morphometric-based feature extraction method of plant leaf (objective-1) and preparing the structure datasets.
3. Deployment of the traditional machine learning algorithms over the structure dataset (objective-2) and finding the various performance measures for the comparison(s).
4. Develop a new approach to achieve effective classification performance using a novel feature extraction method (objective-2).
5. Identifying the future research approach(s) and direction(s).

3.3. NOVELTY OF THE WORK

1. A new feature extraction technique has been developed by fitting curves of various degrees over contour of leaves.
2. Views are created corresponding to each degree.
3. Multiview learning has been deployed on the views created.

4. METHODOLOGY

The methodology for this work includes the following steps which are described in detail in subsections 4.3 to 4.9:

- Preprocessing

- Feature Extraction
- Multiview Construction
- Deployment of ML models
- Performance evaluation

4.1. SCHEME OF PROPOSED METHOD

Flowchart for the standard Multi-view learning model is shown below in figure 4.1 and Figure 4.2 shows the flowchart of early fusion technique for Multi-view Learning which is used for this research work.

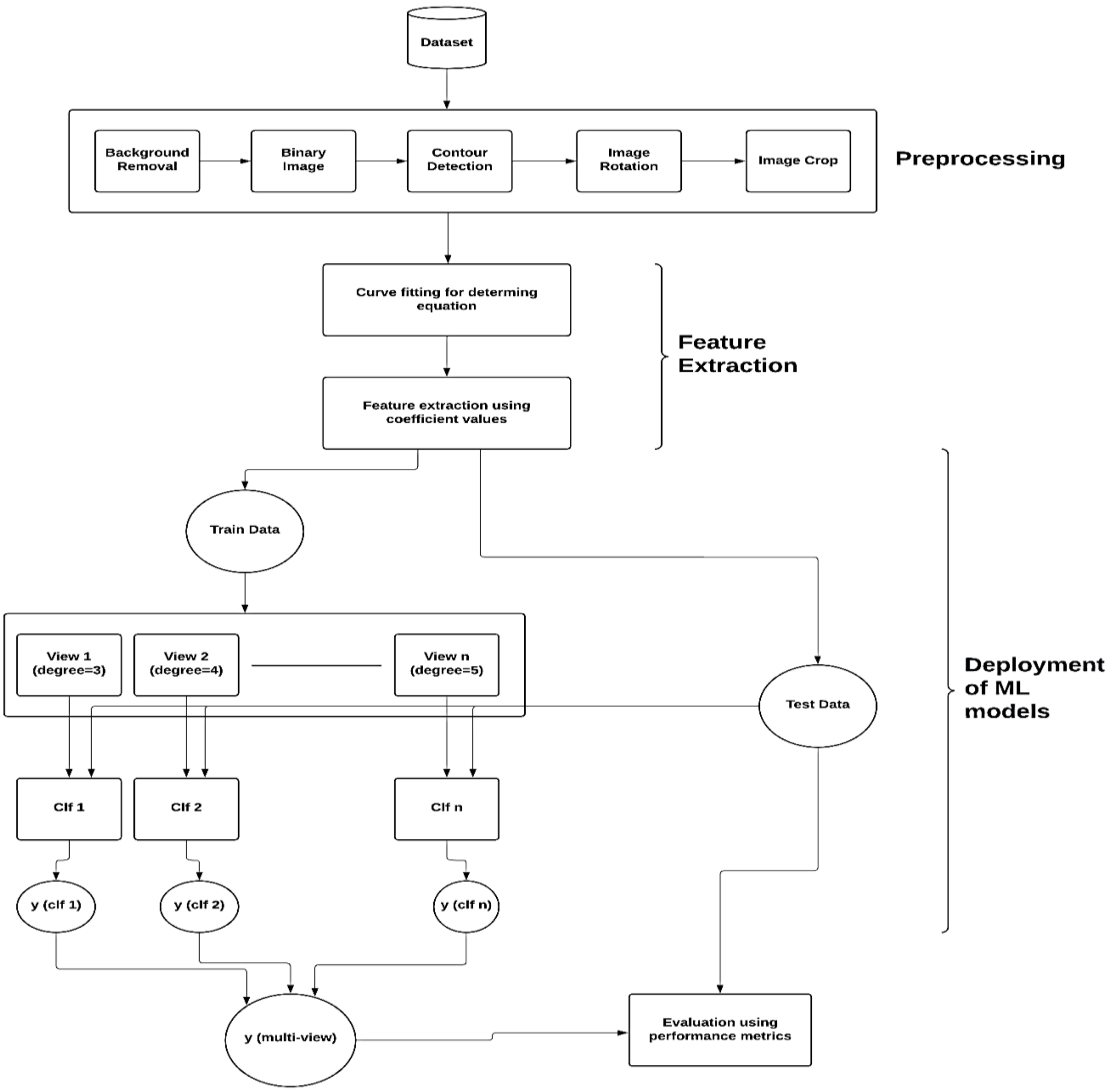


Fig.4.1. Flowchart of Multi-view learning

For early fusion, the flowchart will be as follows:

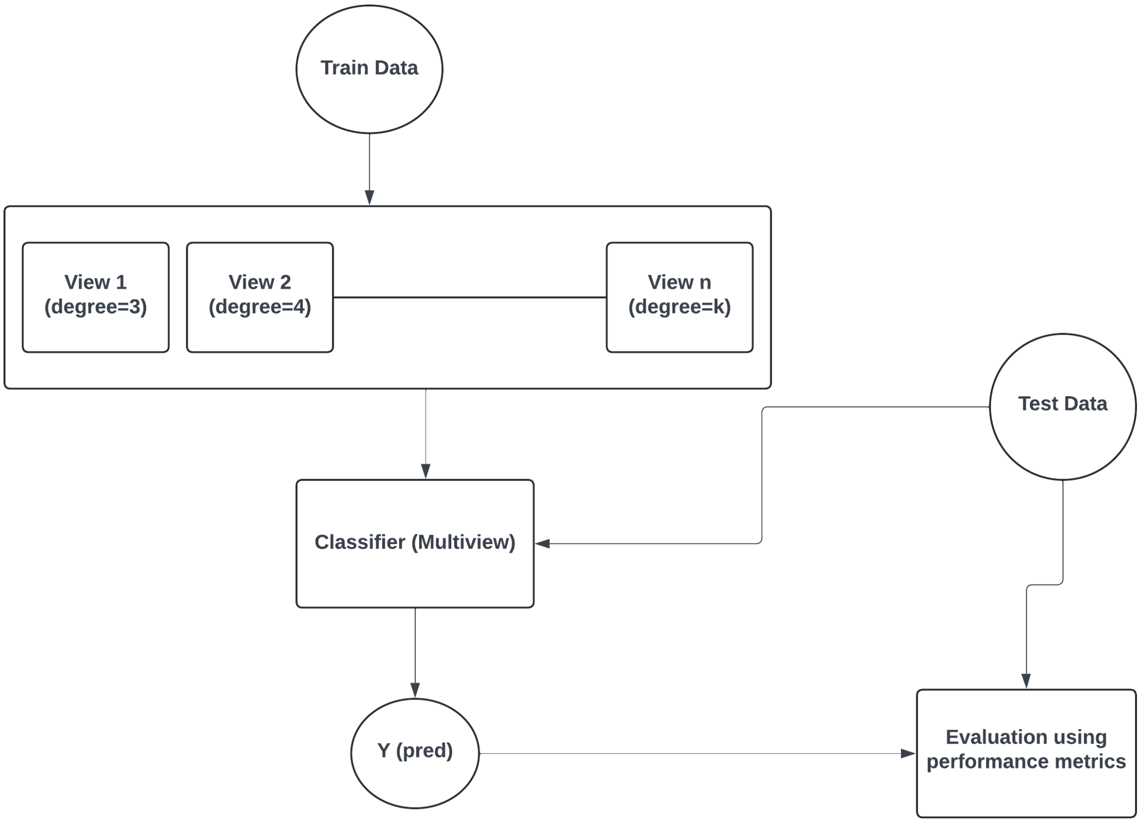


Fig. 4.2. Flowchart of proposed method

4.2. DATASET

Many publicly available leaf datasets, such as Flavia [11], MEW2012[12], and MEW2014, are employed in research as the field of leaf identification becomes increasingly popular. The most commonly utilised dataset for leaf recognition is the Flavia dataset, which comprises 1907 images of leaves belonging to 32 distinct categories. The majority of leaves found in the Flavia dataset are representative of plants native to the Yangtze Delta region. Each species in the dataset is represented by a minimum of 50 leaves, providing an ample amount of data for both training and testing purposes. These images depict individual leaves devoid of a petiole, set against a simple background. In contrast, MEW2012 consists of 9745 leaf photographs encompassing 153 different species, with each species containing between 50 to 99 leaf samples.

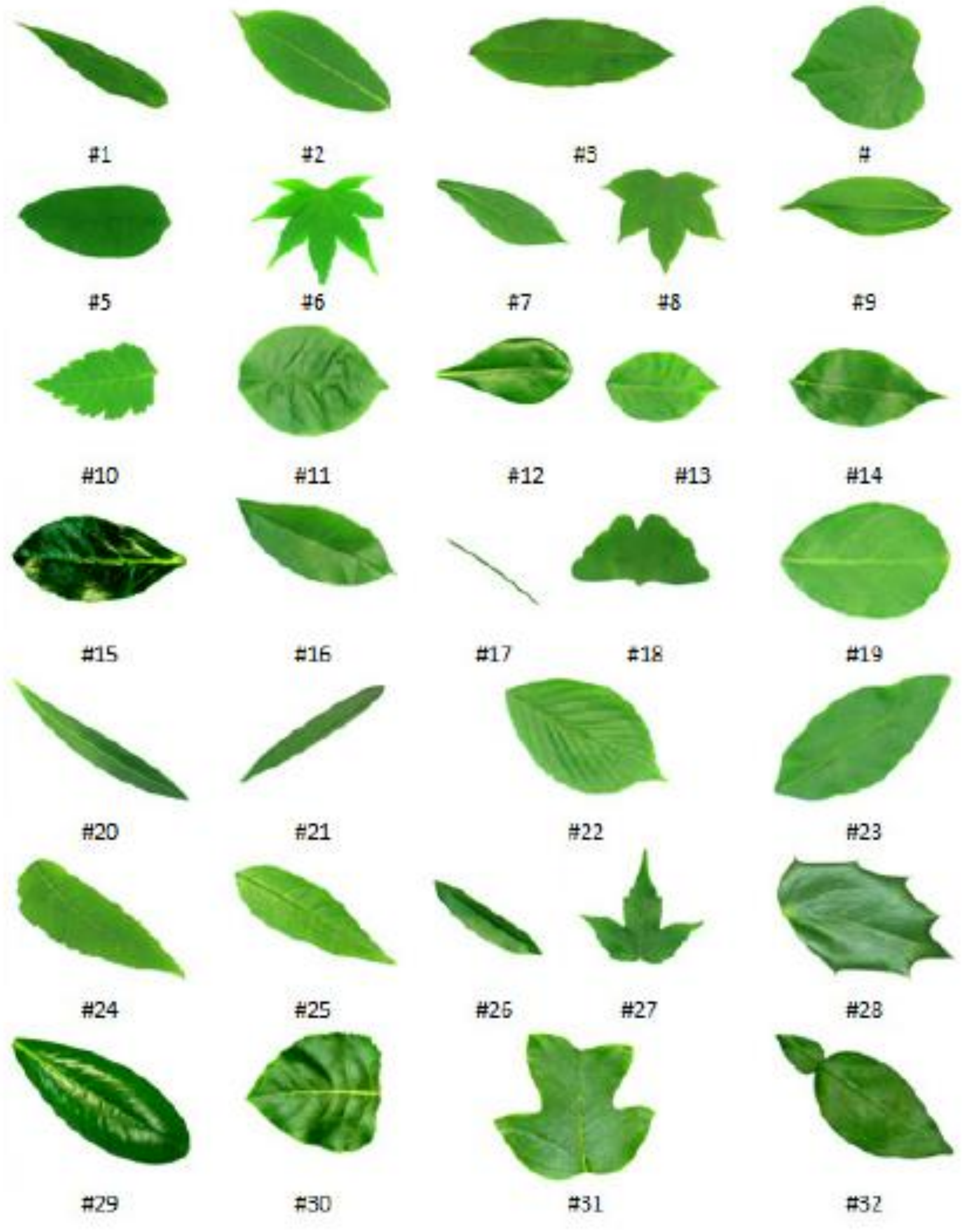


Fig. 4.3. Samples of Flavia Leaves Dataset [13]

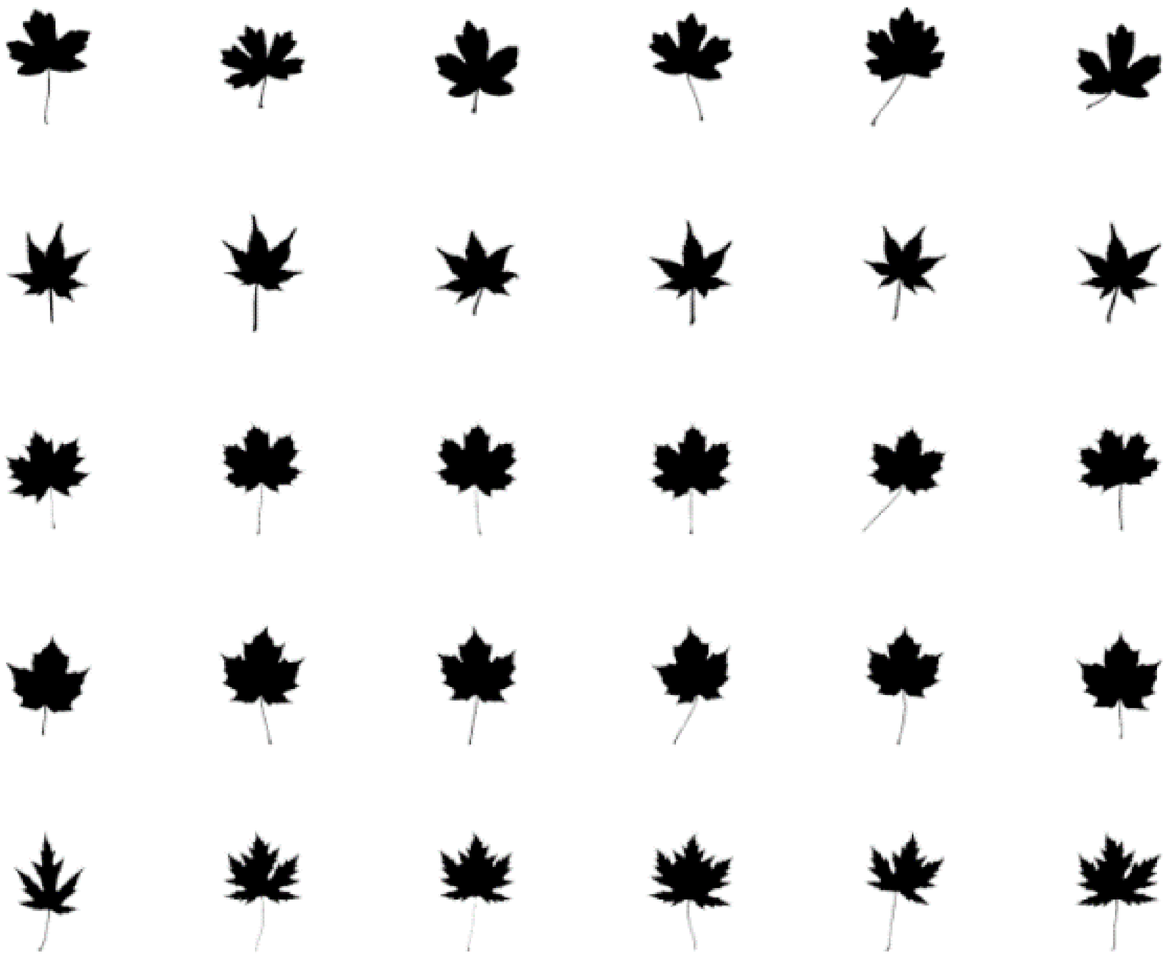


Fig. 4.4. Samples of MEW2012 Dataset [14]

4.3. IMAGE PREPROCESSING

The image needs preprocessing to yield improved outcomes, encompassing denoising, enhancement, and segmentation procedures. If the leaf image contains extraneous background details, it is essential to eliminate this background information to streamline the feature extraction computations. Typically, leaf image datasets are generated using optical scanners, resulting in a background that is straightforward to eliminate through an adaptive threshold segmentation technique. Occasionally, the leaf image may exhibit a complex background, necessitating segmentation to isolate it from the background. Given that numerous leaf images encompass regions devoid of significance, a morphology technique is applied to extract the target region. Subsequently, a quadrilateral shape is utilized to encapsulate the target region, derived by horizontally rotating an outline from the original image. Enhancing the image's contrast and texture is occasionally imperative, involving linear stretching and histogram equalization. The edge and texture of the leaf image are then refined using a high-pass filter on the grayscale image, followed by the extraction of texture features from this grayscale image. Initially, the image is converted to grayscale and then to a binary thresholded image. Further preprocessing is conducted to optimize the algorithm's performance. Binary images consist of pixels with two potential intensity values, often denoted as 0 for black and either 1 or 255 for white. Due to their ability to differentiate between an object's background and foreground, binary images play a crucial role in image processing. During the segmentation process, each pixel can be classified as either "background" or "object," assigned the appropriate black and white hues. Our methodology also involved the elimination of the leaf's sharp contours and internal boundaries.

4.4. BACKGROUND REMOVAL, GREY SCALING AND BINARY IMAGE

The Rembg module is employed for the purpose of eliminating the background from the leaf image within the dataset. By utilizing the Python library, the rembg module, it becomes feasible to extract an image's backdrop. Fundamentally rooted in the Rembg algorithm, this module operates by employing a neural network to effectively eradicate the background. Through extensive training, the algorithm is able to generate transparent backgrounds in images by discerning and distinguishing foreground entities from their surroundings. Leveraging deep neural networks, Rembg accurately identifies the main subject depicted in an image. This innovative technology facilitates precise background removal, thereby enhancing the overall appearance of the image to a refined and professional standard. Furthermore, Rembg accommodates a variety of image file formats such as PNG, JPEG, and GIFs. After the removal of background, the image is converted to grey scale and then binary image is created.

4.5. CONTOUR DETECTION

Edge Detection is a field within the realm of image processing that employs mathematical methodologies to detect edges present in digital images. The process of Edge Detection involves the automatic identification of discontinuities in image regions, such as abrupt alterations in brightness levels or the relative brightness of pixels, through the utilization of a filter or kernel across a digital image. There exist two primary forms of Edge Detection: Search Based Edge detection, which involves the application of the First order derivative, and Zero Crossing Based Edge detection, which incorporates the Second order derivative. The pillow library provides a built-in technique, (ImageFilter.FIND_EDGES), for performing edge detection tasks. Subsequently, the algorithm proceeds to pinpoint pixel coordinates located at the corners of the image. These corners represent the intersection of two distinct image edges and are also recognized as feature points where two principal domain axes converge. Harris corner detection stands out as a widely employed method for corner detection. By systematically moving a window across the image and evaluating the autocorrelation coefficient of the window's area pre and post displacement, it becomes feasible to ascertain the presence of a corner within a particular region. This approach hinges on employing matrices based on first-order derivatives for image-based detection. In essence, a corner denotes a location where the immediate surroundings exhibit notable variations in intensity across all directions. Given their resilience to alterations in viewpoint and lighting conditions, corners hold pivotal importance in the realm of computer vision.

4.6. IMAGE ROTATION

The image is rotated by midrib angle. The midrib angle of a leaf is the angle formed between the midrib (the central vein running along the middle of a leaf) and the horizontal axis. This measurement is commonly utilized in botany to characterize and categorize leaves. The process of determining this angle involves several steps. First, the leaf needs to be separated from its background through techniques like thresholding, edge detection, and colour-based segmentation. The objective is to differentiate the leaf from its surroundings. Subsequently, the binary image of the leaf is skeletonized to reduce the structure's thickness to a single pixel width while preserving the vein connections. Following this, the midrib is detected by identifying the longest continuous line within the leaf's structure, representing the midline. Once the midline is established, the angle can be calculated using trigonometric principles, potentially adjusting it according to the image's coordinate system. The precision of the midrib angle estimation relies heavily on the accuracy of leaf segmentation, skeletonization, and midrib identification.

4.7. IMAGE CROPPING

After rotating the image by midrib angle, the image is vertically divided in two halves: left half image and right half image.

4.8. CURVE FITTING AND FEATURE EXTRACTION

Curves (or equations) of different degrees are fitted on the left half image. Polynomial curve fitting is a mathematical approach for approximating a group of data points by fitting the data to a polynomial equation. The goal is to find a polynomial function closely matching the data point pattern. The fitted curve results in a corresponding equation whose coefficients are stored in a CSV file which is then used to form a feature matrix. Each degree curve has a separate feature matrix which acts as an individual view.

4.9. DEPLOYMENT OF MACHINE LEARNING MODELS

Various machine learning algorithms like LR, KNN, GNB, DT, SVC are applied on each individual view. After calculating the accuracies for each view, Early-Fusion, a multi-view technique is deployed. Early fusion, also known as feature-level fusion, is an approach in multi-view learning where features from multiple views are combined or fused into a single representation before being input to a classifier or learning algorithm.

5. EXPERIMENTAL SETUP

The hardware requirements and software (libraries) used in this research are given below.

5.1. HARDWARE REQUIREMENTS

Specifications of the hardware used for this research work is shown below.

Table 5.1. Hardware Requirements

Component	**Configuration**
Processor	Intel Xeon Silver 4210 CPU-2.19GHz, ten crores
RAM	64 GB
OS	Windows 10 server edition 64-bit
GPU	Quadro RTX 4000

5.2. SOFTWARES USED

Libraries used for this research work are the following: rembg, PIL, os, cv2, numpy, matplotlib, math, lazypredict and sklearn. Parameters used for all the algorithms are default as in lazypredict.

6. RESULTS AND ANALYSIS

6.1. ACCURACY

Below given is the list of the accuracies of the classifiers. Row corresponds to the classifier (LR, KNN, GNB, DT and SVC) and column corresponds to trivial method and various degrees (Degree 2, Degree 3, Degree 4 and Multi-view).

1. FLAVIA

	TRIVIAL	DEGREE-2	DEGREE-3	DEGREE-4	MULTIVIEW
LR.	1.00	0.78	1.00	0.94	**1.00**
KNN	1.00	0.83	1.00	1.00	**1.00**
GNB	0.78	0.72	1.00	0.83	**1.00**
DT	1.00	0.89	0.94	0.94	**1.00**
SVC	1.00	0.67	1.00	0.94	**1.00**

Table 6.1. Flavia dataset accuracy

2. MEW 2014

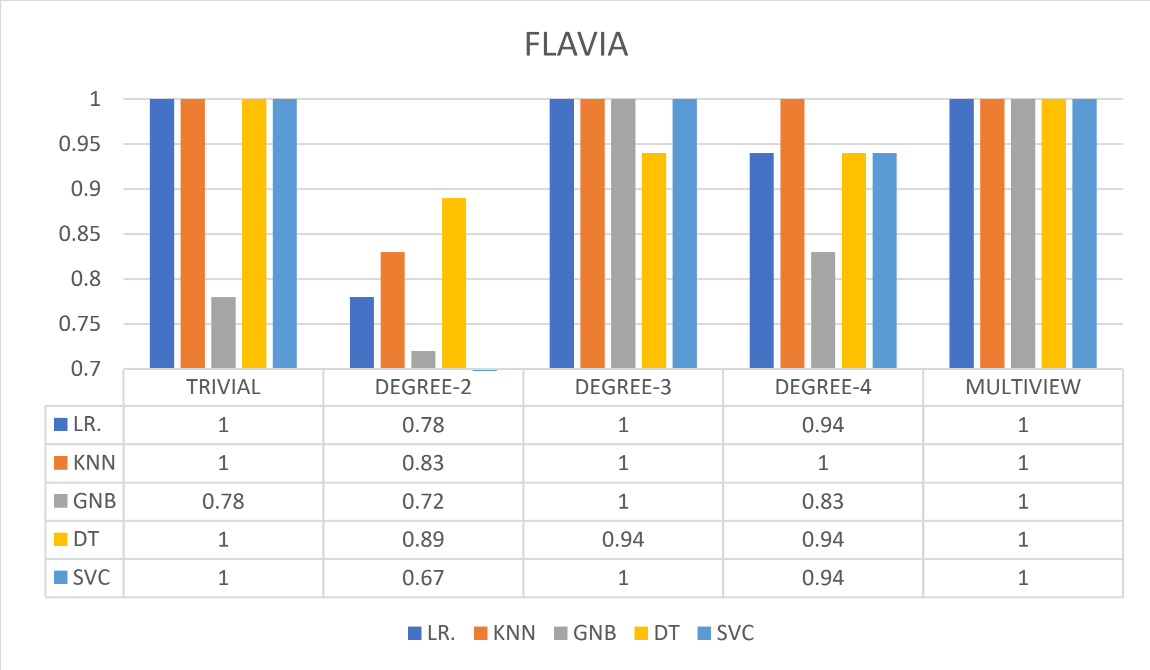
	TRIVIAL	DEGREE-2	DEGREE-3	DEGREE-4	MULTIVIEW
LR.	1.00	0.72	0.44	0.67	0.78
KNN	0.94	0.78	0.83	0.72	0.72
GNB	0.83	0.78	0.56	0.61	0.72
DT	0.89	0.61	0.67	0.67	0.72
SVC	1.00	0.67	0.61	0.72	0.83

Table 6.2. MEW 2014 dataset accuracy

3. MEW 2012

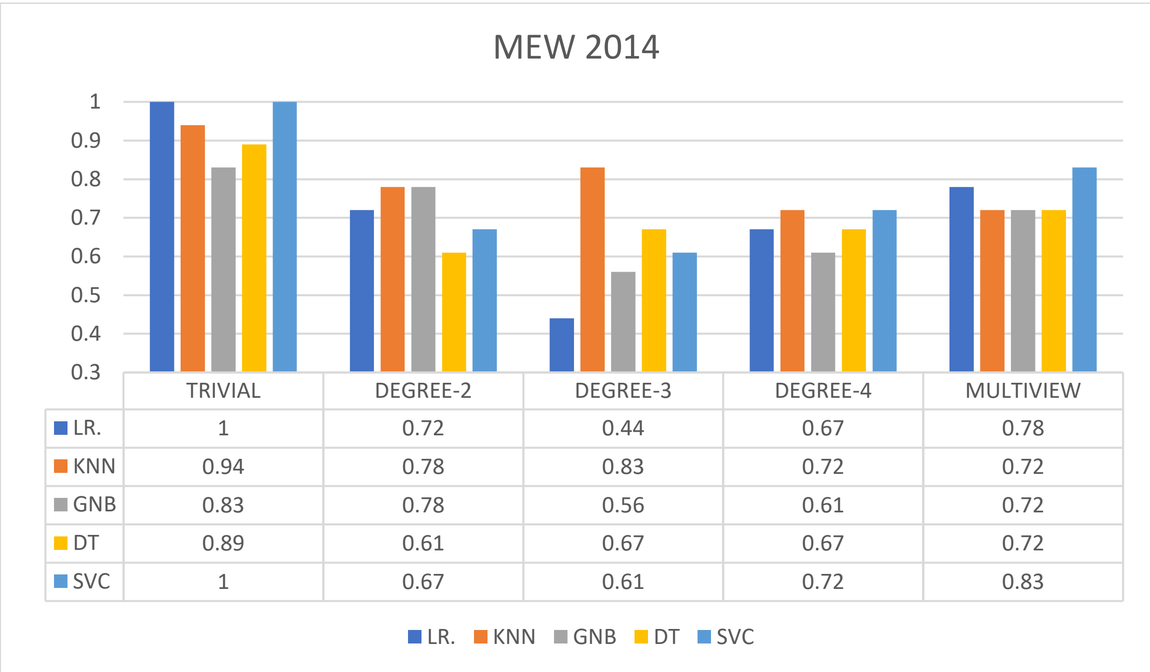
	TRIVIAL	DEGREE-2	DEGREE-3	DEGREE-4	MULTIVIEW
LR.	1.00	1.00	1.00	1.00	**1.00**
KNN	1.00	1.00	1.00	1.00	**1.00**
GNB	1.00	1.00	0.75	0.83	0.92
DT	1.00	1.00	1.00	0.92	**1.00**
SVC	0.96	1.00	1.00	1.00	**1.00**

Table 6.3. MEW 2012 dataset accuracy



	TRIVIAL	DEGREE-2	DEGREE-3	DEGREE-4	MULTIVIEW
LR.	1	0.78	1	0.94	1
KNN	1	0.83	1	1	1
GNB	0.78	0.72	1	0.83	1
DT	1	0.89	0.94	0.94	1
SVC	1	0.67	1	0.94	1

Figure 6.1. Flavia Dataset accuracy



	TRIVIAL	DEGREE-2	DEGREE-3	DEGREE-4	MULTIVIEW
LR.	1	0.72	0.44	0.67	0.78
KNN	0.94	0.78	0.83	0.72	0.72
GNB	0.83	0.78	0.56	0.61	0.72
DT	0.89	0.61	0.67	0.67	0.72
SVC	1	0.67	0.61	0.72	0.83

Figure 6.2. MEW 2014 dataset accuracy

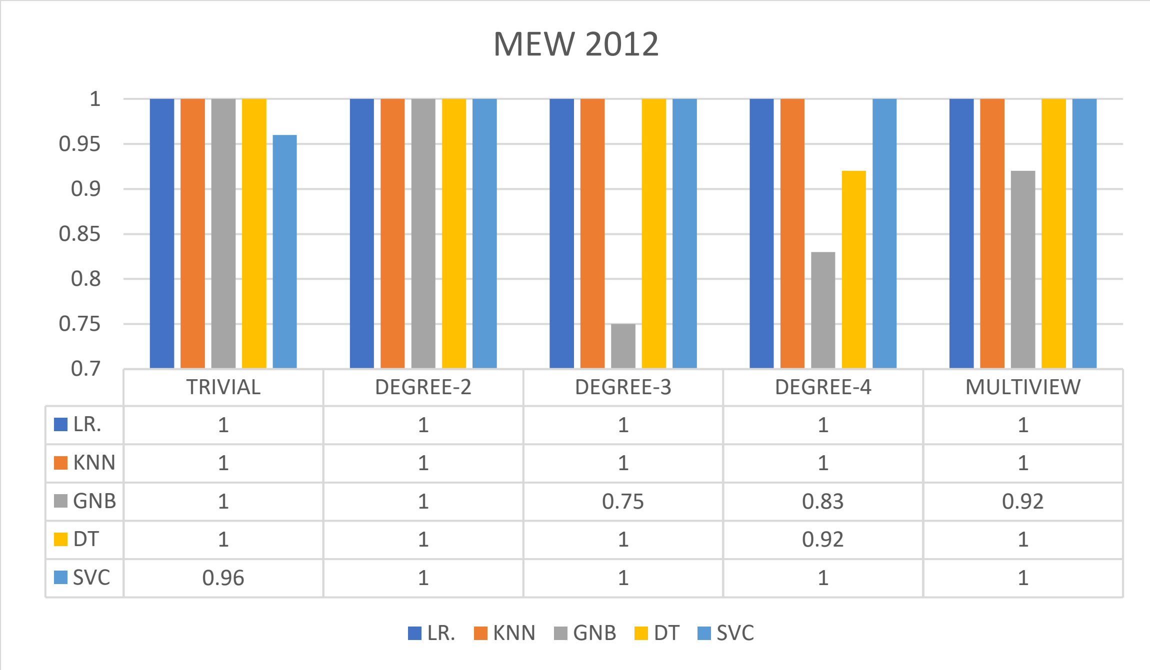


Figure 6.3. MEW 2012 dataset accuracy

6.2. F1 SCORE

Below given is the list of the F1-score of the classifiers. Row corresponds to the classifier (LR, KNN, GNB, DT and SVC) and column corresponds to trivial method and various degrees (Degree 2, Degree 3, Degree 4 and Multi-view).

1. FLAVIA

	TRIVIAL	DEGREE-2	DEGREE-3	DEGREE-4	MULTIVIEW
LR.	1.00	0.78	1.00	0.95	**1.00**
KNN	1.00	0.84	1.00	1.00	**1.00**
GNB	0.78	0.72	1.00	0.84	**1.00**
DT	1.00	0.89	0.95	0.95	**1.00**
SVC	1.00	0.64	1.00	0.95	**1.00**

Table 6.4. Flavia dataset F1-score

2. MEW 2014

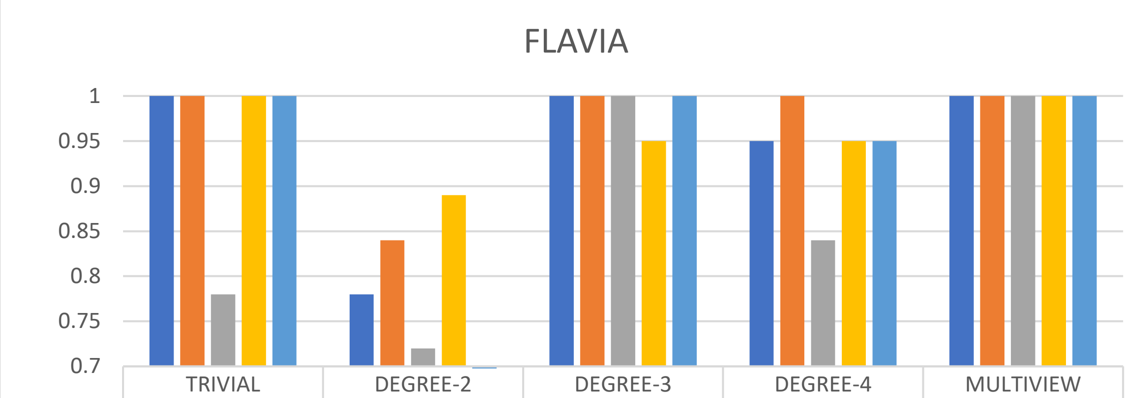
	TRIVIAL	DEGREE-2	DEGREE-3	DEGREE-4	MULTIVIEW
LR.	1.00	0.72	0.45	0.67	0.78
KNN	0.94	0.79	0.83	0.72	0.71
GNB	0.83	0.77	0.57	0.61	0.73
DT	0.89	0.61	0.65	0.63	0.72
SVC	1.00	0.67	0.63	0.73	0.83

Table 6.5. MEW 2014 F1-score

3. MEW 2012

	TRIVIAL	DEGREE-2	DEGREE-3	DEGREE-4	MULTIVIEW
LR.	1.00	1.00	1.00	1.00	**1.00**
KNN	1.00	1.00	1.00	1.00	**1.00**
GNB	1.00	1.00	0.72	0.82	0.92
DT	1.00	1.00	1.00	0.91	**1.00**
SVC	0.96	1.00	1.00	1.00	**1.00**

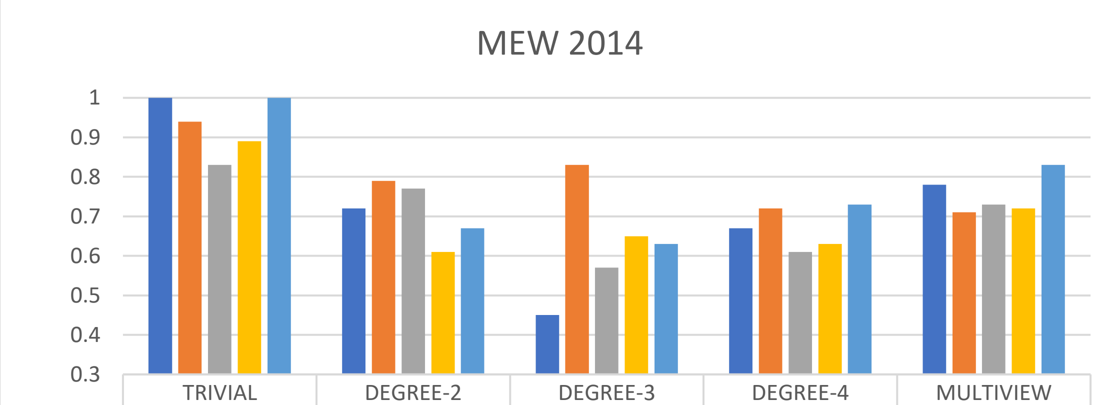
Table 6.6. MEW 2012 dataset F1-score



	TRIVIAL	DEGREE-2	DEGREE-3	DEGREE-4	MULTIVIEW
LR.	1	0.78	1	0.95	1
KNN	1	0.84	1	1	1
GNB	0.78	0.72	1	0.84	1
DT	1	0.89	0.95	0.95	1
SVC	1	0.64	1	0.95	1

LR. KNN GNB DT SVC

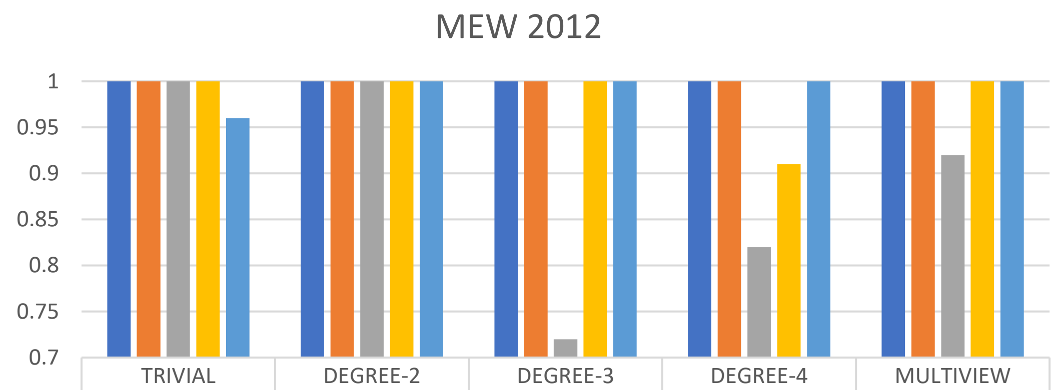
Figure 6.4. Flavia dataset F1-score



	TRIVIAL	DEGREE-2	DEGREE-3	DEGREE-4	MULTIVIEW
LR.	1	0.72	0.45	0.67	0.78
KNN	0.94	0.79	0.83	0.72	0.71
GNB	0.83	0.77	0.57	0.61	0.73
DT	0.89	0.61	0.65	0.63	0.72
SVC	1	0.67	0.63	0.73	0.83

LR. KNN GNB DT SVC

Figure 6.5. MEW 2014 dataset F1-score



	TRIVIAL	DEGREE-2	DEGREE-3	DEGREE-4	MULTIVIEW
LR.	1	1	1	1	1
KNN	1	1	1	1	1
GNB	1	1	0.72	0.82	0.92
DT	1	1	1	0.91	1
SVC	0.96	1	1	1	1

LR. KNN GNB DT SVC

Figure 6.6. MEW 2012 dataset F1-score

6.2. ANALYSIS

For Flavia dataset, Table 6.1 and Table 6.4, shows that Multiview is either better or equivalent to each of the individual degrees. In fact Multiview is even better than trivial method also, where it has performed equivalent to trivial method in case of LR, KNN, SVC and DT and has improved the accuracy of GNB from 0.78 to perfect 1.00 and same with F1-score

For MEW 2014 dataset, tables 6.2 and 6.5 reflect on the fact that Multiview is better than each individual degree except in KNN and GNB where degree-2 has performed slightly better. But trivial method here is better than Multiview and other individual degrees for all the five algorithms.

MEW 2012 dataset shows a surprising result as here degree-2 has scored perfect 1.00 in all the algorithms. Even Multiview and trivial method has similar trend except in SVC where trivial method has accuracy and F1-score of 0.96 and in GNB where Multiview has accuracy and F1-score of 0.92. These facts can be observed from Table 6.3 and Table 6.6.

7. CONCLUSIONS AND FUTURE WORKS

7.1. CONCLUSIONS

A novel feature extraction method based on leaf morphometry equations has been performed to extract multiple views corresponding to different degrees of the equation. Various machine learning models are trained on each view and accuracy is recorded. A Multi-view model is built based on early fusion and its accuracy is compared with other individual views as well as the trivial method. For Flavia dataset, Multiview has achieved accuracy of 100% and hence surpasses the trivial method because trivial has scored only 78% in GNB. For MEW 2014 dataset, Multiview has not performed better than trivial method but is definitely better than each individual degree in most of the cases. MEW 2012 showed a surprising result where degree-2 has 100% accuracy in all the cases.

7.2. FUTURE OBJECTIVES

Future objectives for this research project are as follows:

1. To generate more views by extracting features from higher degrees.
2. To find the best combination of views from the multiple set of views possible.
3. Train other more complex machine learning algorithms and perform cross-validation to identify the best set of parameters for a particular model.
4. Generalize the approach by validating it against more datasets.

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