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Convolutional neural network as an efficient alternative to supervised learners for modelling plant diseases

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Abstract: The high productivity of the agricultural sector is crucial to the Global economy, as well as the national economy. For instance, India increased its nation's GDP by a factor of 17% to 18% in the past few decades. In India, the farming sector is the primary source of income. Numerous insects and illnesses have an impact on plant development, amount, and quality of products. Therefore, it is crucial to find the diseases early in the plant's development. Image processing is used to identify plant diseases and pests. Artificial intelligence, machine learning, and visual analysis have all been used in the past few decades to find and diagnose plant diseases. These computerized techniques are excellent for quickly monitoring vast acreage. In this study, we used the foliage of potato plants to identify diseased leaves affected by early blight, as well as late blight. A Comparison is thus laid between the Convolutional Neural Network (CNN) Model for this purpose, and the standard Supervised Learning Classifiers, like *k* – Nearest Neighbors, Support Vector Machine, AdaBoost, etc. The comparison is subjected not only towards the traditional Metrics, like Accuracy, Precision, etc. but is expanded to temporal domains as well, that is the time taken to compute the results. Also, the training, and testing split used while incorporating the model is another deciding factor in its performance. Several such training–testing splits are considered for such, and thereby, the convolutional Neural Network Model is found to be better in performance than the Supervised Machine Learners irrespective of the Splitting Ratio of the Training, and the Testing Data.

Keywords: Machine Learning, Supervised Learning, Artificial Neurons, Solanum Tuberosum.

Introduction

India is a country of farmers; agribusiness and productive employment account for over sixty per cent of the country's workforce. India's agricultural industry is reliant on the monsoon months Agriculture produces greater quantities when the rainy season is favourable; while when it is bad, farming produces fewer crops or is not in good health. India had the second-largest populace in the world. As a result of expanding populations, farm holdings have been broken up and disorganized, making them unprofitable. Agriculture cultivation in India employs conventional Zhang et al. (2022) techniques and conventional machinery. This is a result of the destitution of individuals and ignorance. Farmers planted a variety of crops on their farms. Here, crops occupy 75% of the land used for cultivation and commercial crops occupy only the remaining 25%. India has two cropping seasons – Rabi, and Kharif, and the monsoon is solely responsible for such. All region's harvest trends are influenced by a variety of variables, including the environment, climate, the system of irrigation, financial drivers, facilities, and social engagement. Agricultural issues are numerous. In India, farming practices remained self-sustaining, but output is still reliant on resources, cereal-centric, and often geographically Gharib and Mandour (2022) biased, raising sustainability concerns. Farmers have been using increasing amounts of pesticides and fertilizers to boost crop yield, but these methods come with a couple of drawbacks; they may negatively affect human health and make people sick; and Bugs will eventually acquire a resistance to the chemicals, rendering them ineffectual over time. 10% of the freshwater we use is for cultivation. New industrial methods need additional water. The manufacturing process of the main crops in India temporarily stops. Due to an enormous discrepancy amid the demands and supplies of the nation's growing population and manufacturing, legislation administrators and administrators are concerned. On one farming operation, the landowner continually harvested the same crop, making it less fertile. Studying the development of vegetation necessitates monitoring of its chemical and physical characteristics. Chlorophyll Najm et al. (2012) as well as nitrogen Johns and Keen (1986) in plant leaves are essential for the development of plants and additionally for gathering knowledge regarding strain and nutrition shortages, as referred by Kumar et al. (2023a). There are two ways we can obtain this knowledge, the traditional approach, in which producers used their unaided vision to examine the development of the plants, nevertheless lacked competence in this field and it is not appropriate for a big region.

Healthy Leaves

Leaves affected by Early Blight

Leaves affected by Late Blight

Fig 1. Pictorial description of a few images from the dataset used for the research. The images in the first row correspond to Healthy Potato Leaves, for the second row, they are affected by the Early Blight Disease, and the third row corresponds to the Late Blight affected Potato Leaves.

This method is both time- and money-consuming. Another option is the usage of recent technical tools such as image processing, machine intelligence, and sensors for remote monitoring. Plants as well as farming fields are negatively impacted by diseases that affect plant leaves. illnesses caused by a variety of microbes, inheritable disorders, and contagious factors such as bacteria, fungi, and viruses. Huang et al. (2019) Potato plant leaves have been utilized in this study. The majority of tuber leaf illnesses are caused by fungi and bacteria. Early and late forms of blight are bacterium-fungal infections and illnesses. The most important agricultural product on the planet is the potato. In India, potatoes are a crop that flourishes in a subtropical environment. It is economical nourishment since it supplies less expensive celery for human consumption. Starch, Vitamin B1, along Vitamin C is all found in potatoes. There are multiple industrial uses for potatoes. Healthy foliage is crucial for potato plants because later on they may produce enough calories for preservation in cellars which will ultimately develop into tubers. To detect the presence of abnormalities on the surface of the tuber, several methods can be adopted, like the Convolutional Neural Networks, and the Classical Supervised Learners. Each of these will have its efficiency and performance to the research problem targeted in this article, but the most important one would be the algorithm that can predict the presence of disease-causing pathogens on the surface of tuber with a higher accuracy than other, and that too without compromising much on the Spatiotemporal domains. Though similar conduct has been made in specific samples of potato leaves, in some existing literature, like Dutta et al. (2023c), and Dutta et al. (2023d) none provokes the variation in efficacy of the detection of disease in the leaves with variation in Training Testing Split. Training Testing split is another important parameter affecting the efficacy and the computational complexities of different algorithms. It is defined as the ratio in which the dataset used for the modelling purpose is split to train the data and the remaining to compute the efficiency of the model when tested on data that is completely naïve to them. The sections that follow declare a brief idea of the nutritional benefits of the Potato tubers, and their biological domains, demonstrate the methods and data used for the research, and further delineate the results obtained as a metric for the comparisons.

Subject of Conduct - Solanum tuberosum

Following the grains of rice, wheat, and cereal grains, potatoes (*Solanum tuberosum*) are the world's fourth-most significant agricultural crop and among the most widely farmed tuber products. The potato, which has a basic set of 12 chromosomes, is a member of the *Solanaceae* category of the genus *Solanum*. In addition to being a popular vegetable, potatoes are also utilized by Jung et al. (2003) to create processed dishes. Potatoes are also utilized in the production of alcoholic beverages and starch. The majority of the main difficulties for potato developers is the creation of cultivars with agronomically significant features and high preservation

Table 1. Tabularization of the results (Training and Testing F1 Score) for each of the algorithms used in the subjection of the research split at a ratio of 80: 20.

Algorithm	Training F1 Score	Testing F1 Score
Support Vector Machine	0.8565161625	0.7558689548
k-Nearest Neighbours	0.8984989894	0.8455262665
AdaBoost	0.9298889589	0.8348948498
Decision Tree	0.8885858549	0.7956561561
Random Forest	0.8800651479	0.7766441393
Gaussian Naïve Bayes	0.8298367466	0.8199964515
Convolutional Neural Network	0.9645556401	0.9535545568

Table 2. Tabularization of the results (Training and Testing F1 Score) for each of the algorithms used in the subjection of the research split at a ratio of 90: 10.

Algorithm	Training F1 Score	Testing F1 Score
Support Vector Machine	0.955294212	0.713040228
k-Nearest Neighbours	0.936950977	0.795431674
AdaBoost	0.957344157	0.735376206
Decision Tree	0.985862861	0.771589815
Random Forest	0.899057662	0.720441287
Gaussian Naïve Bayes	0.921215287	0.762877007
Convolutional Neural Network	0.979980772	0.857674529

qualities. Any crop enhancement effort must first examine the diversity of genes which allowed parents to be chosen to facilitate effective the process of hybridization. The subsequent methods are typically used to evaluate the variation in the genetics of the potato crop populations, like the analysis of morphology, biochemical assessment, as well as genomic indicator study. Goodwin et al. (1994) found limited genetic diversity in processed potatoes; therefore, molecular indicators are essential for evaluating genetic diversification. Adequate genetic indicators should be exhibited in all tissues, organs, and phases of crop growth. They must be at the chromosomal level. When contrasted with conventional breeding initiatives, molecular indicators can boost the efficacy as well as the effectiveness of breeding initiatives. Numerous molecular methods, including RAPD, Microsatellite markers, AFLP, chloroplast RFLP, nuclear RFLP, etc., are used in potato development for many different purposes, including determining the genetic composition of the crop. One of the first crops to be grown for sustenance was the potato. Perennial herbaceous vegetation, the potatoes are grown in moderate, subtropical, and tropical climates. It is a cool season crop in essence. The primary constraining aspect of the cultivation of potatoes is heat. Tuber growth is severely hampered by conditions beneath 10°C (50°F) in addition to 30°C (86°F). An estimated 320 million tons of potatoes are produced worldwide annually as per Haas et al. (2009) over an area of cultivation of around 20 million hectares. Almost thirty per cent of all tubers originate in both India and China, which are currently the world's top two potato producers. As opposed to this, the major potato-producing nations on the continent are Egypt, Algeria, as well as Morocco, according to the sequence. Since the beginning of the twentieth century, the cultivation of potatoes has steadily surpassed that of all other food crops throughout Africa and Asia, claim Haan and Rodriguez. The global production of potatoes is changing significantly. Up before the early 1990s, the majority of tubers were produced and consumed in North America, Europe, and nations in the days when the Soviet Union existed. One of the primary biological limits on the cultivation of potatoes, especially throughout tropical climates in addition to some warmer temperate parts of around the globe, is the presence of pathogenic bacterial infections. Around seven bacterial infections severely harm potatoes, particularly their tubers, which are the plant's most precious resource commercially. The most serious illnesses are thought to be bacterial wilt and back leg, while minor ones as mentioned by Comesaña-Campos and Bouza-Rodríguez (2014) include potato ring rot, as well as common scab. Early blight is a fungal infection caused by *Alternaria solani* which damages tomato as well as potato plants. The disease induces unique bullseye structured spots on foliage in addition to stalk lesions, and potato tuber blight. It additionally causes stalk spots. Although they are called 'early', foliar abnormalities typically appear on older leaves. Early blight may substantially decrease yields if left unchecked. Eliminating prolonged moisture on the foliage and using fungicides are the main strategies for treating this fungal infection. The harmful potato and tomato ailment referred to as late blight or just potato blight is brought on by the oomycete, occasionally referred to as water mould, known as *Phytophthora infestans*.

Results and Discussions

This section discusses the results and possible affirmations from the subject of research. As mentioned in the previous section, for the active contrasting of the results, we included the Deep Learner methodology and convolutional neural Network as a subject of comparison with the classical Supervised Learners, like the k – Nearest Neighbours, AdaBoost, SVM, and others mentioned in Section 3. Also, it was mentioned in the introductory section itself, that the variations in the ratio in which the training and the testing data would be split would incorporate a huge change in the efficiency of the results as shown by these paradigms of Machine Intelligence, similar to Kumar et al. (2023b). For the fruitful classification of the results, we have considered a fledged set of variances in the split ratio, starting with the very traditional 80 – 20 Split, and then paving our way through 90 – 10, 70 – 30, 60 – 40, and finally 50 – 50. All of these splittings were applied to the Convolutional Neural Network model as well since it is also not devoid of the variance that is shown when the ratio is varied. Table 1, 2, 3, 4, and 5 delineates the results following the 90 – 10, 80 – 20, 70 – 30, 60 – 40, and 50 – 50 Split, respectively. For the

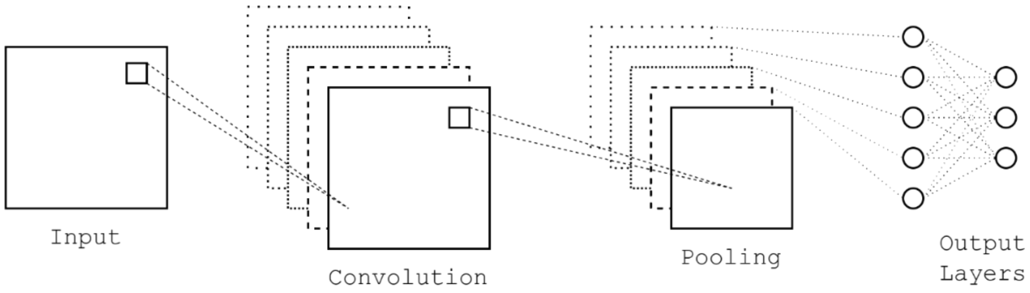

Fig 2. Pictorial description of the Convolutional Neural Network, that is used as an effective alternative to the Supervised Learners.

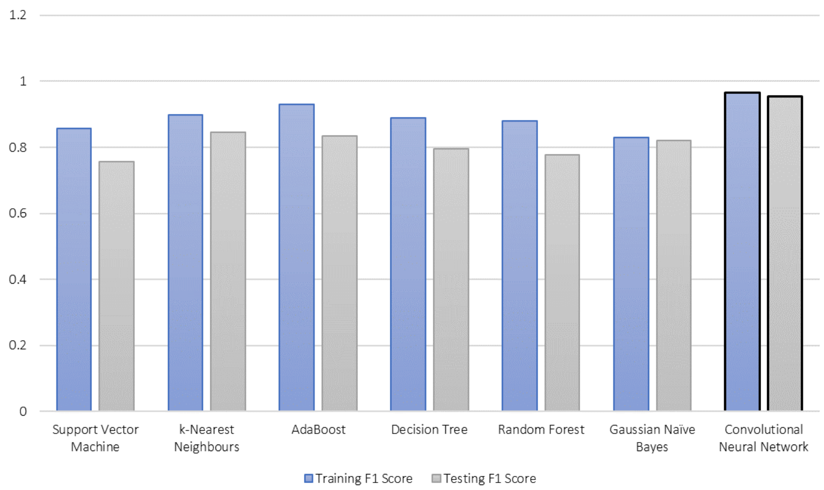

Fig 3. Comparative Plot showing the Training, and Testing F1 Scores for each of the algorithms following 80 – 20 Split.

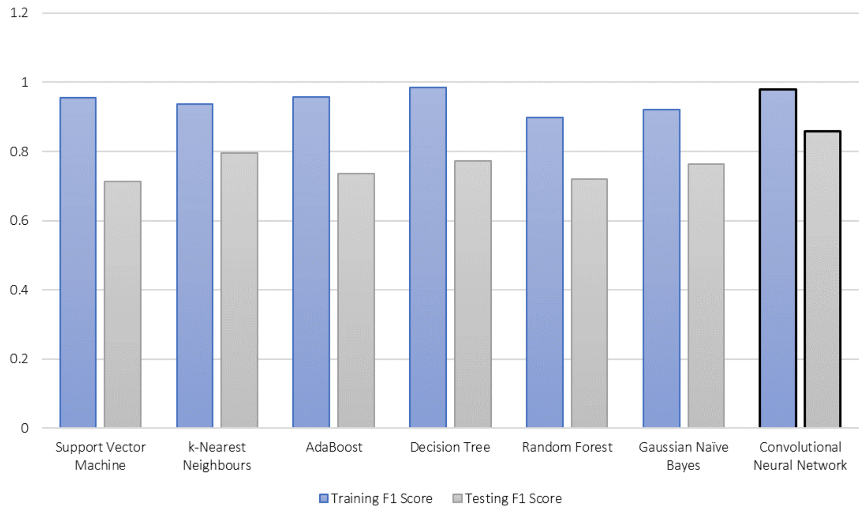

Fig 4. Comparative Plot showing the Training, and Testing F1 Scores for each of the algorithms following 90 – 10 Split.

results, we have considered both the Training, as well as Testing F1 Scores. The predictive ability of a model on an information set is gauged by the F1 score. It is employed to assess binary categorization schemes that label instances as "positive" or "negative." The harmonic average of recall as well as accuracy is the F1 score, following Dutta et al. (2023b). As a result, it systematically captures both recall as well as accuracy in just one measure. Mathematically,

$$F1\ Score\ = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Here, as per Table 1, the Convolutional Neural Network model is attaining the best F1 Score (training, & testing) following an 80 – 20 Split. The respective scores are **0.9645556401** and **0.9535545568,** respectively. None of the Supervised Machine Learning Techniques are quite close.

Here, as per Table 2, the Convolutional Neural Network model is attaining the best F1 Score (training, & testing) following a 90 – 10 Split. The respective scores are **0.979980772** and **0.857674529** respectively. None of the Supervised Machine Learning Techniques are quite close.

Here, as per Table 3, the Convolutional Neural Network model is attaining the best F1 Score (training, & testing) following a 70 – 30 Split. The respective scores are **0.964567282** and **0.861219286** respectively. None of the Supervised Machine Learning Techniques are quite close.

Table 3. Tabularization of the results (Training and Testing F1 Score) for each of the algorithms used in the subjection of the research split at a ratio of 70: 30.

Algorithm	Training F1 Score	Testing F1 Score
Support Vector Machine	0.856659017	0.714521662
k-Nearest Neighbours	0.898647992	0.807341395
AdaBoost	0.930811551	0.744879391
Decision Tree	0.888639116	0.785437865
Random Forest	0.880206083	0.736165843
Gaussian Naïve Bayes	0.829990398	0.767781024
Convolutional Neural Network	0.964567282	0.861219286

Table 4. Tabularization of the results (Training and Testing F1 Score) for each of the algorithms used in the subjection of the research split at a ratio of 60: 40.

Algorithm	Training F1 Score	Testing F1 Score
Support Vector Machine	0.856136526	0.798309418
k-Nearest Neighbours	0.898296927	0.86665668
AdaBoost	0.929158195	0.854418663
Decision Tree	0.887973988	0.841052338
Random Forest	0.879330737	0.817944206
Gaussian Naïve Bayes	0.829787156	0.823036746
Convolutional Neural Network	0.964323775	0.962918509

Table 5. Tabularization of the results (Training and Testing F1 Score) for each of the algorithms used in the subjection of the research split at a ratio of 50: 50.

Algorithm	Training F1 Score	Testing F1 Score
Support Vector Machine	0.86145528	0.751394792
k-Nearest Neighbours	0.90470672	0.757325334
AdaBoost	0.933406051	0.758559854
Decision Tree	0.890346382	0.749717907
Random Forest	0.893686846	0.686962439
Gaussian Naïve Bayes	0.849012948	0.769374064
Convolutional Neural Network	0.967642046	0.922732065

Here, as per Table 4, the Convolutional Neural Network model is attaining the best F1 Score (training, & testing) following a 60 – 40 Split. The respective scores are **0.964323775** and **0.962918509** respectively. None of the Supervised Machine Learning Techniques are quite close.
Here, as per Table 5, the Convolutional Neural Network model is attaining the best F1 Score (training, & testing) following a 50 – 50 Split. The respective scores are **0.967642046** and **0.922732065** respectively. None of the Supervised Machine Learning Techniques are quite close.
Graphical Interpretation of each of these splits and the observations have been noted hereby in the Figure 3-7.
From the tabularization and the figures, it is clear that the Convolutional Neural Network Model is better in performance than the Supervised Machine Learners irrespective of the Splitting Ratio of the Training, and the Testing Data, which is an incremental finding to the existing literature, Dutta et al. (2023c), and Dutta et al. (2023d).

Materials and Methods

In this section, information is laid out about the dataset used for the subject of research and the methodologies used for the same.

Plant materials

The dataset used here in this research consists of 500 images of Potato plants that are healthy, and affected by Early Blight, and Late Blight respectively. It is believed that the sharing of research materials will serve as a better outlet for any research. The dataset used in this research can be availed by reaching out to the corresponding author. Figure 1 is a glimpse of the entire dataset used for research. The first row is composed of some images of Healthy Potato Leaves, the second row of Potato leaves affected by Early Blight, and the third one of leaves affected by Late Blight.

Methodologies

Processing of digital images starts with the acquisition of the images by some sensory medium as mentioned by Smith and Martinez (2011), like the Human Eye or the Camera. Following that, Image Enhancement techniques are introduced in the image to get information about several hidden stats and details in the image, which is followed by the Image Restoration Techniques, in which we make use of mathematical or probabilistic techniques to remove unnecessary noise and interferences in the data. Once the imagery points present inside of the dataset have been passed successfully through the aforementioned steps, we charge them with the necessary algorithms to undertake the Supervised Learning. Here, in this article, we used Support Vector Machine, *k* - Nearest Neighbours, AdaBoost, Decision Tree, Random Forest, and Gaussian Naïve Bayes. Further, we utilized a Convolutional Neural Network to correspond to the research. *Support Vector Machines (SVMs)* are one of the efficient supervised learners that can be applied to both regression and classification-based problems. Finding an axis of separation that optimally isolates the different categories in the simulation data is the basic goal of Support Vectorized Machines. The framework for achieving this is to find a suitable hyperplane with the biggest collateral, indicating the distinction that exists between the hyperplane along with the closest data suites for each class. After scrutinizing the

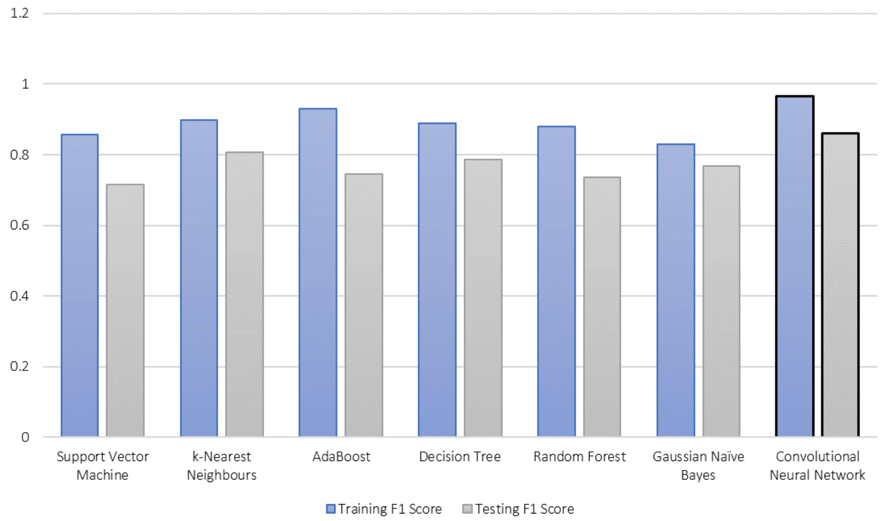

Fig 5. Comparative Plot showing the Training, and Testing F1 Scores for each of the algorithms following 70 – 30 Split.

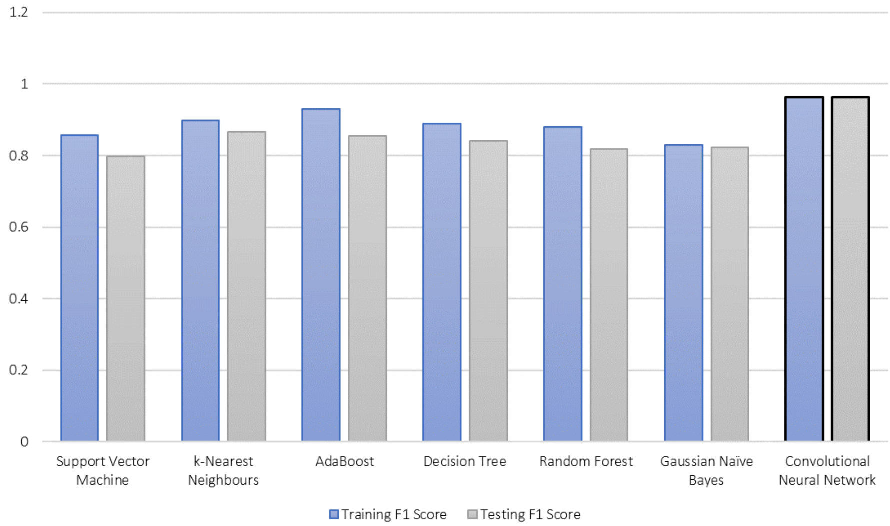

Fig 6. Comparative Plot showing the Training, and Testing F1 Scores for each of the algorithms following 60 – 40 Split.

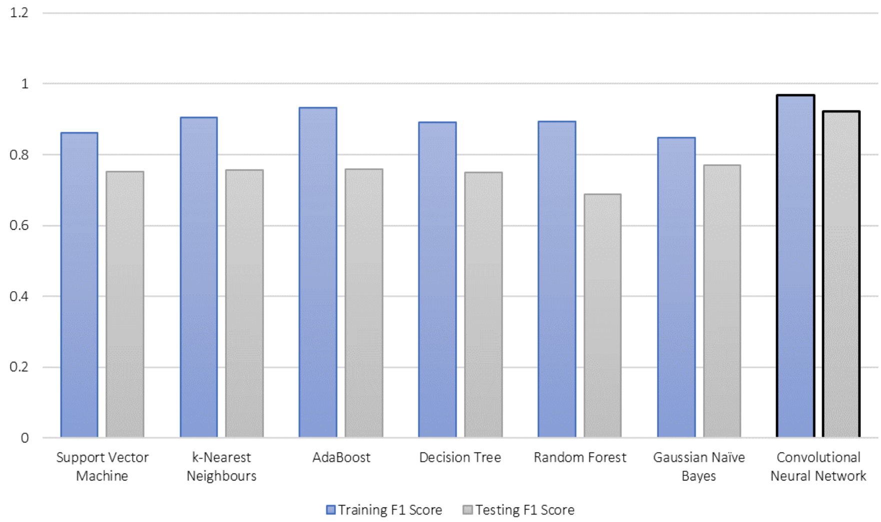

Fig 7. Comparative Plot showing the Training, and Testing F1 Scores for each of the algorithms following 50 – 50 Split.

hyperplane that is efficient enough, fresh, new training data can be categorized by identifying the component of the hyperplane it appears on. When the data includes a lot of features or whenever there is a distinct tolerance of demarcation in the information as in Wang et al. (2022) being analyzed, SVMs are quite helpful. One of the oldest and most fundamental yet crucial categorization methods in machine learning is *k-Nearest Neighbors (kNN)*. It belongs to the area of supervised development and is extensively utilized in the investigation of intrusions, data exploration, as done by Dutta and Saha (2022), and the recognition of patterns. Due to its non-parameterized nature, which means that it makes no fundamental presumptions concerning the pattern of distribution of information, it is frequently used in real-world circumstances. The artificially intelligent meta-algorithm known as *AdaBoost*, or *Adaptive Boosting*, was created by Yoav Freund and Robert Schapire, who additionally earned the 2003 Gödel Prize for their contributions to machine learning. The effectiveness of the algorithm can be enhanced by combining it with a variety of additional instructional techniques. The results of the additional algorithmic methods of learning, or "weak learners," are merged to create an evenly distributed total that corresponds to the enhanced classifier's outcome. AdaBoost is adjustable in that it modifies future weak learners to promote instances that prior classifiers erroneously identified. AdaBoost is cognizant of anomalies and noisy information. It may be less prone to the overfitting issue than other machine learning techniques in particular situations, as raised by Dutta et al. (2023a). It has been demonstrated that the result of the model converges to an effective learner even if the learning outcome of every learner individually is just marginally better compared to arbitrary speculation. AdaBoost using decision trees to serve as poor learners is commonly referred to as being the most effective unconventional classifier. However, every machine learning technique tends to adapt to specific issue forms more effectively than others, and it usually includes numerous distinct settings and arrangements to modify beforehand so it accomplishes its optimum efficiency on an information set. When employed with a decision tree, the AdaBoost technique's data regarding the corresponding "hardness" of every example used for training is introduced into the branch-growing procedure to ensure that subsequent trees prefer to concentrate on cases that are more difficult to categorize, as done by Dutta et al. (2022a). Arguably among the most effective techniques for supervised learning for both regression as well as classification applications is the *Decision Tree*. It creates an organized architecture resembling an organizational diagram wherein every node within the structure symbolizes an evaluation of a characteristic, every branch is a test result, and every leaf node is a class identifier. A limiting requirement, such as the deepest possible level of the structure or the least number of specimens needed for splitting a particular node, is reached by repeatedly separating the data that was used for training into subgroups that correspond to the numerical values of the characteristics. Supremum duo of the countless activities that can be carried out using the effective algorithm for machine learning - "*Random Forest*" are categorization and regression. The randomized forest framework is made up of several tiny decision tree structures, referred to as estimators, each of whose outputs produce a unique set of estimates because it is a consolidation technique. The estimators' estimates are combined by the method of random forest modelling to yield a more accurate forecast, as referenced by Dutta et al. (2022b). *Gaussian Naive Bayes* has its foundation in the principle of Bayes and is utilized for a variety of classification tasks. The further development of Naive Bayes is called Gaussian Naive Bayes. It constitutes a single of Naive Bayes' models for categorization. There is a Gaussian spectrum for information that is continuous. Because of this, we categorize continuous data using the Gaussian Naive Bayes. The Gaussian method makes it simpler to determine the mean as well as the standard deviation concerning the sample information. A particular kind of neural network called a convolutional neural network (CNN) is employed mostly to perform computation and identification of images. A layer of input, layers that are hidden, and an output tier make up this structure. The concealed layers of a network of convolutional neural networks contain any number of layers of convolution. This typically contains a layer that does a dot product operation of the input matrices of the layer that corresponds with the convolutional kernel (refer to Figure 2). Artificial neurons are arranged in numerous layers to form convolutional neural networks. Synthetic neurons are computational operations that determine a stimulation value by summing the weights of various inputs.

Conclusion

Plant Pathology is turning out to be an important pie in modern times. Even if we divulge into the domains of India, we would conclude that, in India, the preliminary source of income for a wide group of individuals is in some way or the other related to the Agricultural Sector. If we can supportively withstand all of the threats that our agricultural sector may face, our economy will be directly helped. The F1 Scores shown in the tables above show the variation of the Training and the Testing Scores with the variation in the Training and Testing Split for each of the Algorithms. It was observed that the Convolutional Neural Networking Model is performing the best for each of the splitting ratios. Though CNNs have been known to work well for these cases of plant pathology, the number of training samples required by the neuronal layers is exceptionally high. ChaosNet is an Artificial Neural Network, which is built on the dynamics of the unit-dimensional Chaotic Generalized Luroth Series, which is known to work well even with a considerably lower number of training samples. The same can be used for the pathological imagery to get the results reunited in a quite minimal threshold requirement. This would help us Economically, Ecologically, Socially, Mentally, and Physically.

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