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# Intelligent Crop Selection and Soil Nutrient Management Using Machine Learning

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***Abstract*—Machine learning employs a wide range of techniques to create models that can foresee yet-to-be-seen data in the future and derive prediction rules from known data, with the use of the same we generate a system that is being suggested to combine information from the meteorological service, grain depository, and soil data to anticipate the most suited crops based on the present state of the environment. The choice of the appropriate crop for the farm's soil conditions is one of the most crucial factors in agriculture. To aid these farmers, a Python prototype of a real-time crop recommendation programme that combines machine learning and data analytics was developed. The ability for computers to learn and adapt without explicit programming is provided by the field of machine learning, falls under the category of artificial intelligence (AI). Traditional disease detection and nutrient value estimation methods are being replaced by a new, more advanced approach that takes advantage of dataset upgrades and looks at the patterns different crops create in response to different climatic conditions. We are collecting data that includes values for the following elements: Nitrogen (N), Potassium (K), Phosphorous (P), Iron (Fe), Zinc (Zn), Copper (Cu), Manganese (Mn), Boron (B), and Sulphur (S) pH, temperature, humidity, rainfall, with the label of crop type for the various districts. High crop yields and the production of high-quality goods depend on the availability of soil nutrients. Therefore, the primary goal of this paper is to provide farmers with a remedy since they frequently administer fertilizer at random without realizing its poor quality or quantity. In order to produce new features, extract them, scale them for the specific ML model, and choose the best one, we provide and place our systematic dataset under numerous machine learning models. In light of this, automatic identification and monitoring are crucial for ensuring sustained agricultural income.**

***Index Terms*—Machine learning, Support vector machine, K- Nearest Neighbours, Soil analysis, NPK sensors, Nutrients analysis, Prediction**

## I. Introduction

The farmers sustain the agriculture system. As is generally known, agriculture plays a crucial role in the growth of a nation. The food sector, which accounts for 18 % of India's GDP and is the foundation of our nation, heavily depends on agriculture. The amount of food grains produced in India is expected to be 292 million tonnes, but the Indian Council for Agricultural Research (ICAR) predicts that by the end of this decade, demand will rise to 346 million tonnes. The usage of pesticides and fertilizers reduces soil fertility due to inadequate infrastructure and improper farming practices [1]. In order to find long-term answers, rural development would need to be reevaluated in light of recent technological developments, and agricultural practices would need to adapt structurally to reflect more effective practices. Indian farmers may experience issues if they don't select the appropriate crops for the land. The use of precision agriculture can help overcome obstacles. A modern agricultural method is precision agriculture which makes crop recommendations to farmers based on site-specific parameters utilizing soil quality research findings, crop production, and soil types [2]. This increases yield and decreases the number of times a crop is picked wrongly. An essential step in determining the nutrients that are available for plants in the soil is soil analysis. Plants use these critical nutrients from the soil to flourish. The results of manual soil testing take many weeks to return from the lab, and even then, the proper crop cannot be anticipated. Choosing the right crops depending on soil nutrients like nitrogen, phosphorus, and potassium concentration is challenging for farmers. Our goal is to develop a prediction engine that can identify the crops that will grow best in a given soil and provide fertilizer that has the minerals those crops need [1]. We regularly test the crops using NPK and atmospheric sensors, and we collect atmospheric conditions from the metrological department. We found that most of the crops were afflicted with harmful diseases and that this necessitated that they be given abnormally high doses of nutrients. As a result, we collected some real-time data that was granularly dependent on the atmospheric conditions from season to season and somewhat on the humidity caused by rainfall. Despite using climatic information to estimate crop yield. Many other input parameters, including as irrigation, fertilizer application, and pesticide treatment, have an influence on yield [3]. Data-driven methods are used in precision agriculture to improve yield prediction. The pH of the soil, the amount of nutrients available, and the temperature all affect predicted yield. Knowing these parameters' threshold levels is essential for a disease-free environment and higher yield production. The farmers will benefit from this as they cultivate crops that are suggested for their soil. Making timely judgments on import and export also benefits from yield production [4]. The dataset's crop information was gathered from a variety of sources, including official websites. With the use of soil sensors, a DHT11 temperature and humidity sensor, an Arduino Uno, and an Atmega CPU, an Internet of Things (IoT) device was built to capture atmospheric data. However, when a comparison study is done between the existing system and the proposed system, there are significant differences in the features used by the proposed model, as well as in how the proposed model determines the correlation between disease-free and diseased crops with the impact of changing atmospheric conditions on changes in nutrient value.

## II. Literature Survey

This portion of the literature study provides a thorough overview of the many types of studies that have been done in relation to crop recommendation and soil nutrients.

1) I extracted the essential NPK (Nitrogen, Phosphorus, and Potassium) values from a specific research paper [5], providing a reliable foundation for the nutrient analysis within my Publication. This paper serves as a valuable reference, contributing to the accuracy and credibility of my research findings and In addition to the NPK values, I sourced other nutrient data on a district-wise basis by referring to another pertinent research paper [6]. This research paper presented a noticeable correlation within the dataset, prompting the need for a dedicated dataset creation process. Leveraging the insights from [6], I initiated the development of a comprehensive dataset that takes into account various nutrients and their distribution across different districts.
2) To anticipate crops, Swati. K et al. [7] took into account characteristics including soil pH, N, P, and K ratios as well as environmental elements like rainfall, weather, humidity, and the area of production. For predicting agricultural yield, machine learning techniques like the CART algorithm and ID3 are employed. Determine the forecast for the chosen crops in the chosen district. The observed accuracy ranges from 90% to 95%. The key drawback of the suggested approach is that prediction is not as precise as anticipated because of the tiny size of the training set. Additionally, abnormalities can occasionally be discovered.
3) "Farmers' Crop Recommender System Based on the Mamdani Fuzzy Inference Model" was created by Kuanr et al. [8] The goal of this research is to develop a collective recommendation system for farmers, to recommend a crop suitable for the farmer's situation in light of weather patterns from earlier months. The Mamdani Fuzzy Inference model is used to implement the proposed system. The results show that it delivers previous crop advice prior to sowing.
4) Jha. K et al. [9] examined the work titled "A comprehensive review on automation agriculture using artificial intelligence." This research discusses the application of several automated practices such as IOT, Machine Learning, and Artificial Intelligence in agricultural systems.
5) RP. Potdar et al. [10] analyzed the work titled Determination of soil nutrients (NPK) using optical techniques. It states that Vis-IR spectroscopy can detect nitrogen, phosphorus, and potassium with R2 0.99, 0.78, and 0.80, respectively. The nutrient content found is as low as 10 R. P. POTDAR ET AL.1 ppm. However, it produced poor predictions for potassium and phosphorus since these elements could not be absorbed directly in the Vis-NIR region.
6) Biswal G.C et al. wrote a white paper titled Crop classification based on macronutrients and meteorological data using machine learning algorithms, and crop success is often dependent on soil type and features. Again, if the soil's micronutrient makeup is as predicted, it aids crop growth. This study demonstrated how to use little soil data to determine a viable crop for a given soil. [11].
7) Shinde. M et al. [12] Developed a mechanism to aid farmers in picking the best fertilizers and crops. Farmers may use this model with Android-based mobile phones. This strategy boosts agricultural production.

## III. PROPOSED SOLUTION

The main goal of this publication is to build and create a yield predictor and estimator for nutrient quantities using machine learning models. The system will track a number of soil characteristics, including crop location, crop nutrient value, and atmospheric condition. After analyzing the data and observing patterns, some new features will also be created and submitted to the ML model. It will be used to teach machine learning. The goal of this study is to visualize various environmental factors so that the precise quantity can be estimated.

The creation of money by precisely determining the amount of fertilizer that should be sprayed on crops, as shown in Fig. 1 calculating the nutritional levels present in that particular crop.

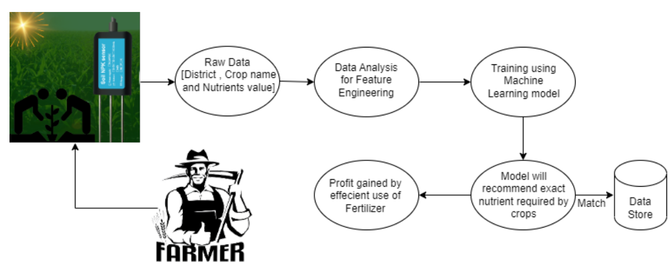


Fig. 1: Proposed Architecture of the System

The heart of our system is built around the use of NPK sensors, temperature and humidity sensors, pH sensors, and an ESP32 microcontroller to seamlessly collect, translate, and send data, which is then aggregated into a CSV file for further analysis. These sensors are strategically placed in the agricultural environment to monitor and quantify key elements that influence plant health and growth. NPK sensors allow us to measure the levels of nitrogen (N), phosphorus (P), and potassium (K) in the soil, providing invaluable insights into soil fertility and nutrient availability.

### A. Dataset Description

The uniqueness of our paper is that we estimate the other nutrient's value by considering copper sensors, Magnesium sensors, and even Nutrient Sensor Array, which helps to calculate the iron and zinc constraints using electrodes. Meanwhile, temperature and humidity sensors provide real-time data on environmental conditions, allowing irrigation and crop tactics

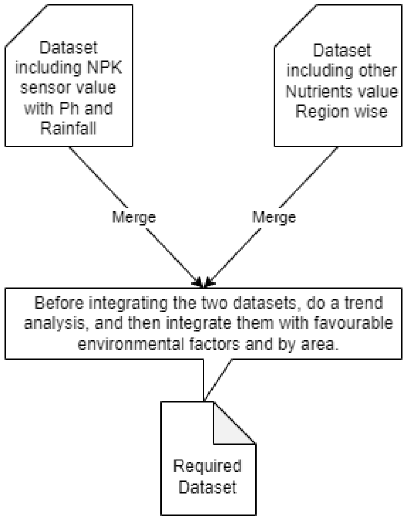


Fig. 2: Needed Dataset

to be optimized. The pH sensors aid in understanding soil acidity or alkalinity, playing a pivotal role in selecting appropriate crops and determining the need for soil amendments. The heart of our data aggregation and transmission system lies in the ESP32 microcontroller, renowned for its IoT capabilities. The ESP32 acts as the central hub, receiving data inputs from a diverse array of sensors. It processes this raw data, translating it into a standardized format for further analysis. One of the key advantages of the ESP32 is its ability to establish Wi-Fi connections, enabling seamless data transfer to the cloud for storage and processing. This two-way communication capability facilitates real-time monitoring, allowing farmers and researchers to make informed decisions promptly. Once the data is received by the ESP32, it is efficiently managed and translated into a comprehensive dataset. To facilitate ease of analysis and compatibility with a wide range of software, the system automatically converts the aggregated data into Comma-Separated Values (CSV) format.

The dataset in Table I below shows a sample of the dataset for Rice that is utilized using the suggested strategy.

### B. Preprocessing of Data

Data preprocessing is the process of transforming raw data into a format for learning algorithms can use to uncover insights or predict outcomes.

The information in Table I was created by combining data from crops grown district-by-district and crops that require nutrients under various environmental conditions. A histogram chart is made to detect whether the data is skewed. The histogram plot reveals that the data is not skewed, and missing values are detected. However, they are in short supply. The mean of the corresponding attribute was used to replace missing values in the dataset. Redundant values, missing values, and other inconsistent data must be removed after gathering the raw dataset. By conducting research and analysis on the dataset, we were able to identify a pattern that repeats itself after a small change in atmospheric conditions. As a result, in the feature engineering section, we created a new feature that calculates the average value of all the nutrients for the specific atmospheric condition, for a specific crop, and district-wise. After determining the average nutrient value for a specific atmospheric condition, we determine the average of all averaged nutrients for the same crop type. This serves as a threshold value, meaning that after deducting the threshold value from the average nutrients for various atmospheric conditions, we are confident in predicting the precise amount of nutrients needed by the specific crop at a specific time in a specific district (NAR). Now that we have seen some positive and negative values, we can determine if the crops' nutrient requirements are too high or too low. The quantity needed by the crops or an excess of nutrients present in the crop field is indicated by positive and negative values.

### C. Adverbial model

Before passing our generated dataset to the ML model, we used the scikit learn module's train_test_split() method to partition the dataset into a training dataset and a testing dataset. Training and testing are essential components of creating a machine-learning model. During the training phase, the model is exposed to labeled data to help it comprehend patterns and relationships. During the testing phase, the model's ability to generalize and create correct predictions beyond its training data is evaluated using other, previously unknown data.

Due to their adaptability and favorable qualities, Support Vector Machines (SVMs) are a preferred option for nutrient value prediction in crop-related research. SVMs perform exceptionally well in tolerating complex nutrient-soil-climate cycles typical in agricultural contexts, as well as linear and non-linear connections between input characteristics and goal nutrient levels. Their resistance to overfitting is especially useful when working with noisy and sparse agricultural information. Furthermore, the effectiveness of SVMs in handling outliers is consistent with the unpredictability frequently observed in agricultural data. SVMs may use feature engineering to include domain knowledge, making it possible to create relevant features that capture complex nutrient-crop relationships. For accurate nutrient forecasts in novel crop situations, SVMs' balance between margin maximization and error reduction encourages models that generalize skillfully to new, unknown data. Even though SVMs have unique advantages, the best model to use depends on several variables, including the dataset's features, the difficulty of the task, and the available computing power. This calls for a thorough evaluation of SVMs and other models that are better suited to the particular agricultural setting [13].

Support Vector Machines formulation

Support Vector machines are used to realize the ideas that were previously stated. To see why, we must first describe the loss functions and the hypothesis spaces used by SVM. It is a common misconception that SVM determines an ”optimal” hyperplane as the solution to the learning problem. The linear SVM formulation, in which the hyperplane is located in the space of the input data x, is the most straightforward [14]. In this case, the hypothesis space is a subset of all hyperplanes with the formula

TABLE I: Crop and Nutrient Value Sample Dataset for Rice

| District | Zn % | Fe % | Cu % | Mn % | B % | S % | N | P | K | Temp | Hum. | pH | Rainfall | NAR | Label |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anantapur | 67.67 | 65.14 | 91.88 | 77.70 | 73.54 | 85.90 | 90 | 42 | 43 | 20.88 | 82.00 | 6.50 | 202.94 | -3.87 | rice |
| Chittoor | 80.51 | 78.19 | 99.77 | 91.82 | 89.04 | 88.62 | 85 | 58 | 41 | 21.77 | 80.32 | 7.04 | 226.66 | -12.22 | rice |
| East Godavari | 79.27 | 88.14 | 95.54 | 97.24 | 88.05 | 95.67 | 60 | 55 | 44 | 23.01 | 82.32 | 7.84 | 263.96 | -11.21 | rice |
| Guntur | 58.30 | 71.16 | 98.86 | 91.40 | 86.15 | 86.81 | 74 | 35 | 40 | 26.49 | 80.16 | 6.98 | 242.86 | -4.49 | rice |
| Krishna | 78.62 | 82.02 | 98.05 | 95.23 | 65.78 | 98.56 | 78 | 42 | 42 | 20.13 | 81.60 | 7.63 | 262.72 | -8.70 | rice |

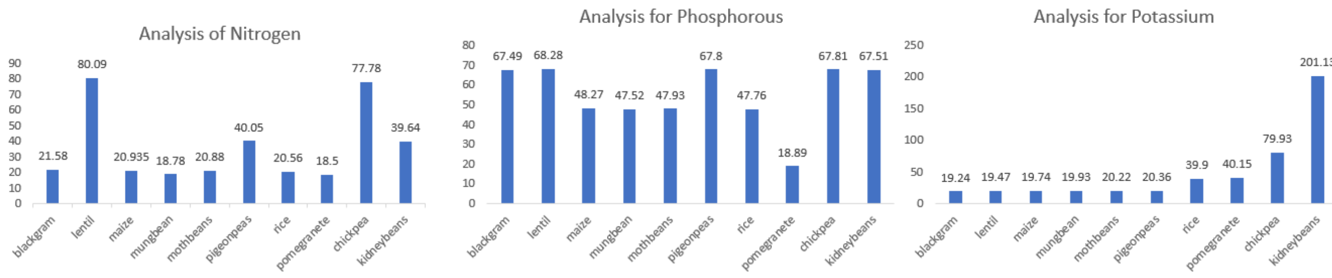


Fig. 3: Nutrients Analysis

**f(x) = w*x + b**

We utilize the RBF kernel in our SVM model to handle the fact that the underlying relationship between features and targets is complicated and non-linear since we are unsure whether or not our data set is linearly separable. We notice that our data set is not very high dimensional and analyze the fact that it produced a polynomial pattern, therefore in the future, we will also include poly kernel in our SVM model, and we will be able to achieve the accuracy of 99%,underscoring the efficacy of SVM in addressing this critical agricultural challenge. By harnessing the power of machine learning and kernel-based SVM algorithms, we demonstrate the potential to revolutionize nutrient management practices in agriculture, ultimately fostering sustainable crop production and food security. This research not only advances the field of precision agriculture but also offers valuable insights for policymakers and farmers seeking to optimize crop nutrient utilization and minimize environmental impacts.

Another Model that we will consider in our study is KNN (K-Nearest Neighbours) In this an item is categorized by a majority vote of its neighbors, with the object being given to the class that has the highest percentage of commonality among its bits k closest neighbors. It is also a strong competitor for forecasting nutrient values necessary for crop development, mostly because of its capacity to recognize regional trends and take into account a variety of data distributions. KNN's process is consistent with the idea that similar crops with comparable nutrient requirements tend to cluster in close proximity within feature space, which is important in the field of nutrient prediction because the nutrient requirements of crops are impacted by a variety of contextual and environmental factors. This attribute is crucial since it enables the model's ability to deduce nutrient requirements by locating nearby examples with comparable development circumstances. KNN performs particularly well in the presence of complex and non-linear interactions, enabling it to efficiently adjust to the complex dependencies that underpin nutritional needs.

Our predictive KNN model had a test accuracy of 91.89% and a train accuracy of 95.12%. These findings show that our model, as demonstrated by its excellent test accuracy, demonstrates a significant power to generalize unknown data.

For Further Advancement, we propose the implementation of a parallel deep learning model to optimize execution time. This involves the integration of GRU (Gated Recurrent Unit) cells within the hidden layer of the neural network, a strategic move to conserve memory usage. The distinctive feature of GRU cells lies in their efficient management of internal memory, retaining only essential data and eliminating the superfluous. GRU cells primarily serve as short-term memory units, and their utilization of gates enables precise control over information flow.

Furthermore, we introduce a novel variant known as Parameterized Rectified Linear Unit (ReLU) in the hidden layers of the neural network. This innovative approach introduces an additional parameter, affecting the slope of the function's negative segment. This enhancement significantly contributes to the accuracy of classification. Our overarching objective in this study is to develop a neural network model capable of predicting and classifying soil fertility indices with heightened precision.The implementation was carried out by dividing the dataset into two halves, A and B, for micro and macro. The dataset was then evaluated based on error rate, and the outcomes were compared for various algorithm systems [15]. In order to assess the efficacy of our suggested model, we carefully examined the dataset by splitting it into two parts, A and B, which stand for the macro and micro features, respectively. Error rates were the main focus of the assessment procedure, and the results were carefully compared with different algorithmic approaches. Interestingly, our method demonstrated remarkable accuracy, indicating a noteworthy breakthrough in the field of soil fertility prediction. The model has the potential to transform nutrient management and precision agricultural methods due to its high degree of accuracy in classifying soil fertility metrics. Indeed, our results showed an exceptional 89% accuracy rate, confirming the stability and effectiveness of the GRU-integrated parallel deep learning model and the novel Parameterized ReLU, which together improve the model's performance and classification accuracy.

### D. Results

TABLE II: Techniques for predicting nutritional values and recommending crops using machine learning

| Reference/Author | Techniques Used | Comments/Accuracy |
|---|---|---|
| K.Patel et al. [16] | SVM | Precision, recall, and F1 accuracy score of 97.65%. |
| A.Suruliandi et al. [17] | Feature Extraction, KNN, Naive Bayes, Decision tree, SVM, Random Forest, Bagging | Adoption of more accurate prediction techniques is necessary. |
| N.H. kulkarni et al. [18] | Naive Bayes, Linear SVM, Algo., Random Classifier | For a select few harvests only increased precision. |
| T.V.N. rao et al. [19] | Decision Tree (DT), Random Forest | Real-time forecasts and quick processing. Learning features. |
| V. Pandit et al. [20] | KNN, NB Multinomial, Logistic Regression, Random Forest | KNN algorithms forecast mustard crop production with more accuracy. |
| J. Chavan et al. [21] | Naive Bayes, Decision Tree | Information about geography and climate. In the future, seed and fertilizer recommendations can be included. |
| P.Parameswar et al. [22] | PART algorithm, JRip, Decision table | Impressive results achieved with the PART algorithm: high accuracy at 98.33%. |
| Krupa Patel | SVM | 97.65% |
| Rao and others | Decision Tree (DT), Random Forest | 94% |
| Nidhi H Kulkarni | Naive Bayes, Linear SVM | 98% |

Refer to Table-II to see how accurate the other study report was and in the realm of nutrient prediction modeling, the empirical results showcased in Table-III illuminate the distinct accuracies achieved through the deployment of diverse algorithms. This juxtaposition of algorithmic methodologies not only sheds light on their individual performances but also underscores the nuances and intricacies associated with each approach. The Support Vector Machine (SVM) generated a respectable accuracy of 99.1% when combined with the Radial Basis Function (RBF) kernel. This achievement demonstrates the power of the SVM-RBF combo in effectively identifying complicated patterns within data, allowing for strong nutritional forecasts. Equally noteworthy, the SVM employed in tandem with the polynomial kernel exhibited an even higher accuracy of 99.5%. This outcome underscores the adaptability of the SVM framework, showcasing its ability to adapt and excel under differing kernel configurations. This remarkable accuracy attests to the model's proficiency in discerning and mapping complex nutrient relationships. While SVM performed admirably, the k-nearest Neighbours (KNN) algorithm followed suit with a significant accuracy of 95.1%. This result demonstrates KNN's ability to find patterns within a dataset based on proximities, which contributes greatly to the nutrient prediction process. In relation to Table- II, our model is the best with high accuracy, handling all nutrient values of the crop as well as non-linearity of the dataset, making our model more efficient.

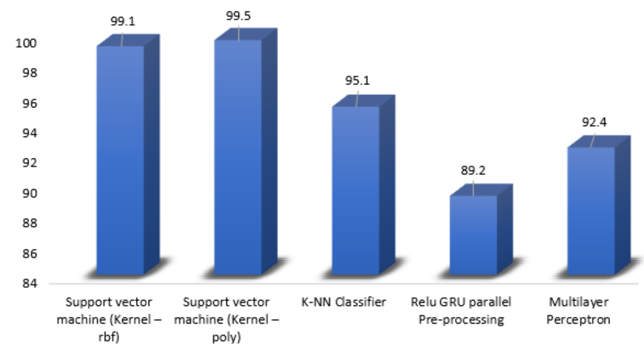


Fig. 4: Presentable Research work Representation

TABLE III: COMPARISON OF VARIOUS ALGORITHMS FOR PREDICTING THE VALUE OF NUTRIENTS APPLIED IN THIS PAPER

| **Model** | **Accuracy** | **F1-Score** | **Precision** | **Recall** |
|---|---|---|---|---|
| Support vector machine (Kernel – rbf) | 99.1% | 0.991 | 0.993 | 0.989 |
| Support vector machine (Kernel – poly) | 99.5% | 0.995 | 0.994 | 0.996 |
| K-NN Classifier | 95.1% | 0.951 | 0.955 | 0.947 |
| Relu GRU parallel Preprocessing | 89.2% | 0.892 | 0.891 | 0.893 |
| Multilayer Perceptron | 92.4% | 0.924 | 0.922 | 0.926 |

Furthermore, in the pursuit of comprehensive algorithmic exploration, a Multi-Level Perceptron (MLP) was implemented in our study, yielding a commendable accuracy of 92.4%. The inclusion of the MLP underscores our commitment to a diverse approach, leveraging neural network architectures to capture nuanced relationships within the data. This achievement contributes valuable insights into the model's capability to navigate complex patterns, reinforcing its efficacy in predicting nutrient requirements for crops. It's crucial to note that the implementation of the MLP provides an additional layer of sophistication, further enriching the overall predictive capacity of our model. This multi-faceted approach ensures a robust and comprehensive understanding of nutrient prediction in agricultural settings.

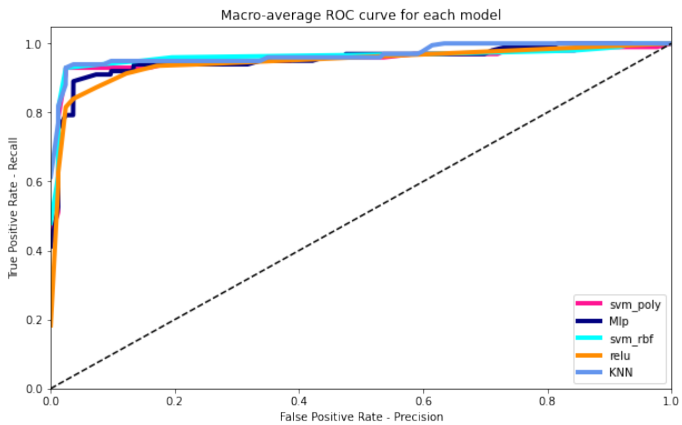


Fig. 5: ROC curve Representation

## IV. CONCLUSION

The fact that agriculture is the foundation of our nation is universally acknowledged. Farmers currently face many challenges in agriculture, and they lack trustworthy information on the crops and fertilizers they will grow and apply to the crops. Several writers offered suggestions on how to make farmers profitable while also assisting them in realizing how much nutrition their crops contain and how much fertilizer their crops require. Researchers are also working on the best crop recommendation to make it easy for farmers not to think so much, which they can't due to a lack of knowledge, so farmers benefit from that. The suggested Model figures out the ratio of nutrients in a soil sample taken from a farm and suggests how much fertilizer should be applied in what amounts to feed the soil in a specific location and for a certain crop. The suggested technique enables farmers to store a significant amount of fertilizer for use on future crops while maximizing production for the current crop cycle. Lowering the likelihood of overfertilization, this also guarantees that healthy crops have been grown. Our model is analyzing the dataset and observes some correlation and variance between the different features. Using the same, our model contains some new calculated features that can handle the nonlinearity of the dataset. Even though our dataset covers almost all of the nutrients present in the majority of the soil, we expect some sort of advancement in our model that can see the more underlying pattern or correlation between the dataset and do some feat. The system we use has certain drawbacks. First of all, even though we included some new features, the sample size was insufficient to support the whole number of features we have. However, we may still improve the sample size. Without this restriction, the system may operate more effectively since there would be less chance of the model overfitting the data. Second, the dataset does not cover the entire agricultural system because our Indian area is mostly known for rice and a few other crops, therefore the class distribution for different crop labels is biased.

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