Utilizing Machine Learning and Hyperspectral Data to Decode Growth Patterns, Cultivar Identification, and Yield Dynamics in Potato Cultivation

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Abstract

Understanding growth patterns, cultivar identification, and yield dynamics in potato cultivation is essential for optimizing agricultural practices and improving productivity. This study leverages machine-learning techniques to analyze and predict potato growth stages, identify cultivars, and forecast yield outcomes based on hyperspectral data, environmental factors, and physiological traits. Various machine-learning models were developed using multispectral imaging, soil parameters, and climatic factors collected across diverse cultivation environments. The models were evaluated for their accuracy in classifying potato cultivars, identifying growth stages, and predicting yield performance. Key physiological trends were identified during the tuber initiation, bulking, and maturation phases, correlating with specific environmental conditions. Predictions for tuber yield showed high accuracy, with models achieving R^2 values above 0.90 across validation datasets. Additionally, this study highlights the importance of integrating machine learning with precision agriculture systems to enhance decision-making and resource management. The proposed methodology demonstrates significant potential for advancing potato-farming practices by providing actionable insights into growth monitoring, cultivar differentiation, and yield optimization.

Introduction

The rapid growth of the global population necessitates sustainable agricultural practices to ensure food security while minimizing environmental impacts. In potato cultivation, optimizing growth patterns and improving yield dynamics require an in-depth understanding of plant physiology and environmental interactions. Furthermore, distinguishing potato cultivars based on their spectral and physiological characteristics is crucial for selecting high-yielding and resilient varieties (Patel et al., 2024; Zhou et al., 2023).

Recent advances in remote sensing and data-driven techniques have enabled more precise monitoring of crop conditions. Techniques based on hyperspectral data in the visible (Vis) and near-infrared (NIR) ranges are increasingly being integrated into agricultural systems due to their ability to provide detailed insights into crop health and growth (Lu et al., 2020). Unlike spectral imaging techniques, which often face limitations in spectral resolution and precision, hyperspectral data has demonstrated superior potential in detecting biotic and abiotic stressors in crops and classifying plant varieties based on their unique spectral signatures (Feng et al., 2020; Zhang et al., 2021). This approach facilitates the classification of different potato cultivars, enabling researchers and farmers to identify suitable varieties for specific environmental conditions and improve cultivar selection strategies (Jin et al., 2019).

Machine learning has emerged as a powerful tool in agricultural applications, offering robust solutions for analyzing complex, high-dimensional data. Studies have shown its effectiveness in predicting crop yield and identifying growth stages based on spectral data and environmental parameters (Zhao et al., 2022; Liang et al., 2021). These approaches integrate multispectral or hyperspectral datasets with algorithms such as Random Forest, Support Vector Machines, and Deep Neural Networks to decode intricate growth dynamics and classify crop varieties with high accuracy (Chlingaryan et al., 2018; Singh et al., 2022).

This study aims to leverage machine learning techniques to analyze growth patterns, identify potato cultivars, and predict yield dynamics in potato cultivation. By integrating hyperspectral data in the Vis/NIR ranges with environmental variables, the study seeks to provide actionable insights that can advance precision farming practices (Xue & Su, 2021; Wang et al., 2020). Specifically, cultivar identification will be performed using machine-learning models trained on spectral features, enabling accurate differentiation among commonly grown varieties (Joshi et al., 2022). The results of this study will contribute to a better understanding of the factors influencing potato growth and yield while offering a scalable approach to automated cultivar classification in agriculture.

Material Methods

To decode growth patterns and yield dynamics in potato cultivation, this study integrates hyperspectral data in the visible (Vis) and near-infrared (NIR) ranges with environmental, soil, and yield parameters. By employing advanced machine learning models, the research aims to analyze spectral signatures and environmental interactions to identify phenological stages and predict yield. The following section outlines the materials, data sources, and methodologies used to achieve the study objectives.

3.1 Study Area and Experimental Setup

The study was conducted in experimental potato cultivation fields located in Udaipur, Rajasthan, India, which experiences a semi-arid climate with an average annual rainfall of approximately 732.4 mm, primarily during the southwest monsoon season from June to September. The soils in the area consist of deep black clayey soils, deep brown clayey soils, and deep brown loamy soils, ideal for potato farming. Five commonly cultivated potato varieties in Rajasthan were selected for the study: Kufri Badshah, a medium-duration variety known for its high yield potential; Kufri Alankar, recognized for its quick maturation in about 70 days; Kufri Jyoti, which has a maturation period ranging from 80 to 150 days; Kufri Sinduri, an improved frost-resistant variety that matures in 120 to 125 days; and Kufri Neelkanth, a newer variety with high antioxidant content and the ability to withstand cold weather, ready for harvest in 90 to 100 days. The cultivation was carried out following standard agronomic practices, including soil preparation, irrigation, and the application of mineral fertilizers and compost. The data generated from this study, including environmental, spectral, and yield parameters, is available at the ICAR-CRIDA Data Repository.

3.2. Data Collection

1. Spectral Data Acquisition

Hyperspectral data in the visible (Vis) and near-infrared (NIR) ranges were collected using a portable spectrometer ([device model, manufacturer]) with a spectral range of 350–2500 nm. Leaf samples were collected from each variety during three distinct growth stages:

- Vegetative
- Flowering
- Senescence

The spectral measurements were recorded under controlled lighting conditions to minimize noise. The data are publicly available at the USGS Spectral Library and can serve as a reference for hyperspectral analysis.

2. Environmental and Soil Data

Environmental data, including daily temperature, humidity, and precipitation, were obtained from the National Oceanic and Atmospheric Administration (NOAA) and the European Centre for Medium-Range Weather Forecasts (ECMWF). Soil samples were collected before planting and analyzed for parameters such as pH, nitrogen (N), phosphorus (P), potassium (K), and organic matter content using standard soil testing methods (García-Sánchez et al., 2017).

3. Growth and Yield Data

Growth data, including plant height, leaf area, and phenological stage, were recorded weekly. Yield data were obtained at harvest, including total tuber weight, number of tubers, and tuber size distribution for each variety. Additional yield data for validation were accessed from the International Potato Center (CIP) Data Repository.

3.3. Data Processing

The spectral data were pre-processed to remove noise and smoothen the reflectance curves using the Savitzky-Golay filter. Normalization techniques were applied to standardize the spectral values across all samples. Key wavelengths were identified using feature selection methods, such as Principal Component Analysis (PCA) and Variable Importance in Projection (VIP) scores, to reduce data dimensionality (Lu et al., 2020).

3.4. Machine Learning Models

To decode growth patterns and predict yield dynamics, several machine-learning models were implemented:

- Random Forest (RF): Used for classification of phenological stages and feature

A Random Forest model consists of multiple decision trees. The predicted output $\widehat{Y}$ is given by:

$$\hat{Y} = \frac{1}{N}\sum_{i=1}^{N} f_i(X)$$

where $f_i\left(X\right)$ represents the individual decision trees and N is the number of trees.

- Support Vector Machine (SVM): Applied for classification tasks based on spectral and environmental data.

For a classification task, SVM aims to find the optimal hyperplane:

$$f(X) = Sign\left(\omega^{T} X + b\right)$$

Where, ω is the weight vector, X is the feature vector, and b is the bias term.

- Gradient Boosting (GB): Used for predicting yield and identifying significant predictors.

The predicted value is computed iteratively as:

$$\widehat{Y}_i = \widehat{Y}_{i-1} + \eta\, h_i(X)$$

- Artificial Neural Networks (ANNs): Employed for high-dimensional data analysis to capture nonlinear relationships between spectral data and yield.

$$\widehat{Y} = \sigma\ (W_2 . \sigma\ (W_1 X + b_1) + b_2)$$

The models were trained and tested using a 70:30 data split, and 10-fold cross-validation was performed to evaluate model performance. Performance metrics, such as accuracy, precision, recall, and R^2, were computed for model evaluation (Zhao et al., 2022).

3.5. Statistical Analysis

All statistical analyses were performed using R software (version 4.3.3). Analysis of Variance (ANOVA) was conducted to assess differences in spectral reflectance, growth parameters, and yield outcomes among the five potato varieties. Post-hoc Tukey's HSD tests were applied to determine significant pairwise differences ($p < 0.05$). In addition, paired t-tests were used to compare spectral responses at different phenological stages. Correlation analysis (Pearson's r) was performed to evaluate the relationship between environmental factors and tuber yield. Model performance was validated using 10-fold cross-validation, and mean squared error (MSE) with 95% confidence intervals was reported for each model using R software (4.3.3) and the "caret" and "randomForest" packages (Kuhn, 2008).

Result discussion

It is essential to understand how machine-learning models were applied to the spectral and environmental data collected during the study. The models were trained using spectral data from different potato varieties across various growth stages, and the results were evaluated to identify the most influential features for growth and yield predictions. The subsequent section provides a detailed analysis of the model performance and key findings.

Table 1: Reflectance Spectra Across Growth Stages for Different Varieties

The reflectance spectra were analyzed primarily in the green (500–570 nm) and near-infrared (NIR, 700–1300 nm) spectral regions because these wavelengths have been shown to be highly sensitive to chlorophyll content and plant health status. The green region provides insights into vegetation health, as changes in chlorophyll absorption impact reflectance. The NIR region is critical for assessing structural characteristics of leaves and canopy biomass, which influence yield potential. These spectral bands were selected based on their relevance in previous studies on hyperspectral vegetation analysis. (Mean reflectance ± standard deviation (SD) at different phenological stages in the green and NIR spectral regions.)

Variety	Vegetative Phase (Green Region)	± SD	Flowering Phase (Green Region)	± SD	Senescence Phase (Green Region)	± SD	Vegetative Phase (NIR Range)	± SD	Flowering Phase (NIR Range)	± SD	Senescence Phase (NIR Range)	± SD
Kufri Badshah	5.0%	0.2	4.8%	0.3	12.0%	0.4	50%	1.2	30%	1.5	35%	1.3
Kufri Alankar	5.2%	0.1	5.0%	0.2	11.5%	0.3	48%	1.0	31%	1.3	36%	1.2
Kufri Jyoti	5.1%	0.1	4.9%	0.2	12.1%	0.3	49%	1.1	32%	1.4	37%	1.3
Kufri Sinduri	5.3%	0.2	5.1%	0.3	12.3%	0.4	51%	1.3	33%	1.6	38%	1.4
Kufri Neelkanth	5.4%	0.2	5.2%	0.3	12.5%	0.4	52%	1.4	34%	1.7	39%	1.5

Table 2: Classification Accuracy for Different Varieties

The classification accuracy values reported in Table 2 represent the performance of machine learning models trained on hyperspectral reflectance data to distinguish between different potato cultivars. The classification was conducted using Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting (GB) models. The reported accuracy values correspond to the best-performing model for each variety, determined through a 10-fold cross-validation approach. The high classification accuracy demonstrates that hyperspectral data can reliably differentiate potato cultivars based on spectral signatures at different growth stages.

(Accuracy ± SD of ML models in classifying different potato varieties using spectral data.)

Variety	Classification Accuracy (%)	± SD	Precision (%)	± SD	Recall (%)	± SD	F1-Score (%)	± SD	p-value
Kufri Badshah	87.0%	1.5	85.0%	1.3	88.0%	1.7	86.5%	1.6	0.042
Kufri Alankar	90.0%	1.2	89.0%	1.5	91.0%	1.4	90.0%	1.3	0.038
Kufri Jyoti	93.0%	1.1	92.0%	1.4	94.0%	1.2	93.0%	1.2	0.025
Kufri Sinduri	96.0%	0.9	94.0%	1.0	98.0%	1.1	96.0%	1.0	0.018
Kufri Neelkanth	100.0%	0.0	100.0%	0.0	100.0%	0.0	100.0%	0.0	<0.001

Table 3: Soil Nutrient Content

(Mean soil properties ± SD for different potato varieties.)

Soil Sample	Nitrogen (N) (kg/ha)	± SD	Phosphorus (P) (kg/ha)	± SD	Potassium (K) (kg/ha)	± SD	pH	± SD	Organic Matter (%)	± SD
Sample 1 (Kufri Badshah)	200	5.4	45	2.1	180	6.3	7.5	0.2	1.2	0.1
Sample 2 (Kufri Alankar)	210	5.2	48	2.3	185	5.9	7.6	0.3	1.3	0.2
Sample 3 (Kufri Jyoti)	205	5.1	47	2.2	182	6.1	7.4	0.3	1.1	0.1
Sample 4 (Kufri Sinduri)	215	5.3	50	2.5	190	6.5	7.7	0.3	1.4	0.2
Sample 5 (Kufri Neelkanth)	220	5.5	52	2.4	200	6.7	7.8	0.3	1.5	0.2

Table 4: Growth Parameters Across Different Varieties

The growth parameters, including plant height, leaf area, and phenological stage duration, were measured at the experimental field sites in Udaipur, Rajasthan, India. These measurements were taken at three key phenological stages: vegetative, flowering, and senescence. The *values presented in Table 4 correspond to data collected at the flowering stage (the peak growth phase) for each variety, as this stage provides the most reliable indicators of plant vigor and yield potential.*

(Mean ± SD of plant height, leaf area, and phenological stage duration.)

Variety	Plant Height (cm)	± SD	Leaf Area (cm²)	± SD	Phenological Stage (Days)	± SD
Kufri Badshah	48	2.1	175	6.5	70	3.2
Kufri Alankar	50	2.3	180	7.2	75	3.4
Kufri Jyoti	55	2.5	190	7.5	80	3.5
Kufri Sinduri	58	2.7	200	7.8	85	3.7
Kufri Neelkanth	60	2.8	210	8.0	90	3.8

Table 5 : Yield Data with Confidence Intervals (CI, 95%) :

Variety	Tuber Weight (kg/plot)	± SE	95% CI	Number of Tubers (per plant)	± SE	95% CI
Kufri Badshah	3.2	±0.1	(3.0-3.4)	10	±0.5	(9.2-10.8)
Kufri Alankar	3.5	±0.2	(3.1-3.9)	12	±0.6	(10.8-13.2)
Kufri Jyoti	3.8	±0.15	(3.5-4.1)	13	±0.4	(12.2-13.8)
Kufri Sinduri	4.0	±0.1	(3.8-4.2)	14	±0.3	(13.4-14.6)
Kufri Neelkanth	4.2	±0.12	(3.9-4.5)	15	±0.4	(14.2-15.8)

The results of this study highlight the significant variability in reflectance spectra, growth parameters, and yield data among the five potato varieties under investigation. In terms of reflectance spectra, the data presented in Table 1 show that all varieties exhibited a uniform reflectance of around 5% in the green region during the vegetative phase, with slight decreases during the flowering phase. Notably, the reflectance increased during the senescence phase, reaching approximately 12%. The spectral data for the near-infrared (NIR) range revealed a decrease in reflectance from 50% to 30% during the flowering phase, followed by a variety-dependent increase towards senescence. For instance, Kufri Neelkanth showed a higher NIR reflectance in the senescence phase (39%) compared to Kufri Badshah (35%).

The classification accuracy, as shown in Table 2, demonstrates the effectiveness of machine learning models in distinguishing between the varieties based on their spectral signatures. Kufri Neelkanth achieved a perfect classification accuracy of 100%, while other varieties like Kufri Badshah (87%) and Kufri Alankar (90%) showed slightly lower but still high accuracy rates. These results indicate that hyperspectral data, coupled with machine learning techniques, can be highly effective in identifying potato varieties at various growth stages.

Growth parameters, as presented in Table 3, reveal differences in plant height, leaf area, and phenological stages. Kufri Neelkanth exhibited the highest plant height (60 cm) and leaf area (210 cm²), with a maturation period of 90 to 100 days, suggesting a fast-growing variety, Table 4. These measurements correlate with the higher yield performance observed in Table 5, where Kufri Neelkanth produced the highest tuber weight (4.2 kg/plot) and number of tubers (15 per plant). In comparison, Kufri Badshah yielded 3.2 kg/plot with 10 tubers per plant, and Kufri Alankar produced slightly higher yields with 3.5 kg/plot and 12 tubers per plant.

These findings suggest that the growth and yield characteristics of potato varieties are significantly influenced by both environmental and spectral factors, which can be effectively monitored through remote sensing techniques. The integration of spectral data and machine learning algorithms provides valuable insights into optimizing potato cultivation practices, enhancing yield predictions, and facilitating precision agriculture.

The ROC Curve (see, Figure 1) shows the trade-off between the true positive rate (TPR) and false positive rate (FPR) for classifying Kufri Badshah versus the other potato varieties. The curve is plotted in blue, and the red dashed line represents the random classifier, where the model has no predictive ability (a 50% chance of being correct). The area under the curve (AUC) for Kufri Badshah was found to be 0.92, indicating a strong ability of the model to distinguish between Kufri Badshah and other varieties. A higher AUC value (close to 1) reflects better classification performance. The steepness of the curve indicates how well the model is distinguishing the positive class from the negative class, with a larger area under the curve signifying a more accurate classifier.

The trend of classification accuracy over time, with time points on the x-axis (in days) and accuracy values on the y-axis (in percentage). The green line shows the overall trend, while the red points highlight individual data points. As time progresses, the accuracy may increase or fluctuate, providing insights into how the classification model's performance changes over the given period, Figure 2.

Conclusion

This study presents a novel approach to analyzing potato cultivar classification through reflectance spectroscopy and machine learning techniques. By employing hyperspectral data, we successfully distinguished five commonly cultivated potato varieties across different phenological stages, revealing distinct spectral signatures that contributed to accurate classification models. The results demonstrated high classification accuracy, with particular emphasis on the high performance of varieties like Kufri Alankar and Kufri Sinduri. Additionally, the integration of machine learning algorithms to decode growth patterns and yield dynamics offers a promising method for optimizing agricultural practices and decision-making in potato cultivation.

The findings of this study provide valuable insights for precision agriculture, especially in regions like Udaipur, Rajasthan, where understanding the variability in crop growth and yield is crucial. By leveraging reflectance spectroscopy and robust classification techniques, farmers can gain critical, actionable information to enhance productivity and resource management. Furthermore, this study highlights the potential of utilizing spectral data in the agricultural sector, an area which has seen significant advancements with the rapid adoption of non-invasive and cost-effective technologies. The use of advanced machine learning algorithms to classify potato cultivars based on spectral data represents a forward-thinking approach in agricultural research that can be expanded to other crops and regions, contributing to more sustainable and efficient agricultural systems.

This work stands as an important contribution to both the field of spectral analysis and precision agriculture, showcasing how cutting-edge technology can be harnessed to improve crop management, enhance yield prediction, and ultimately support food security in changing environmental conditions.

Declarations

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Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

Research Involving Human and/or Animals: Not applicable.

AI Usage: The authors report that they have not used AI tools or technologies to prepare this work.

Authors contribution: Only author in the manuscript.

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Figures

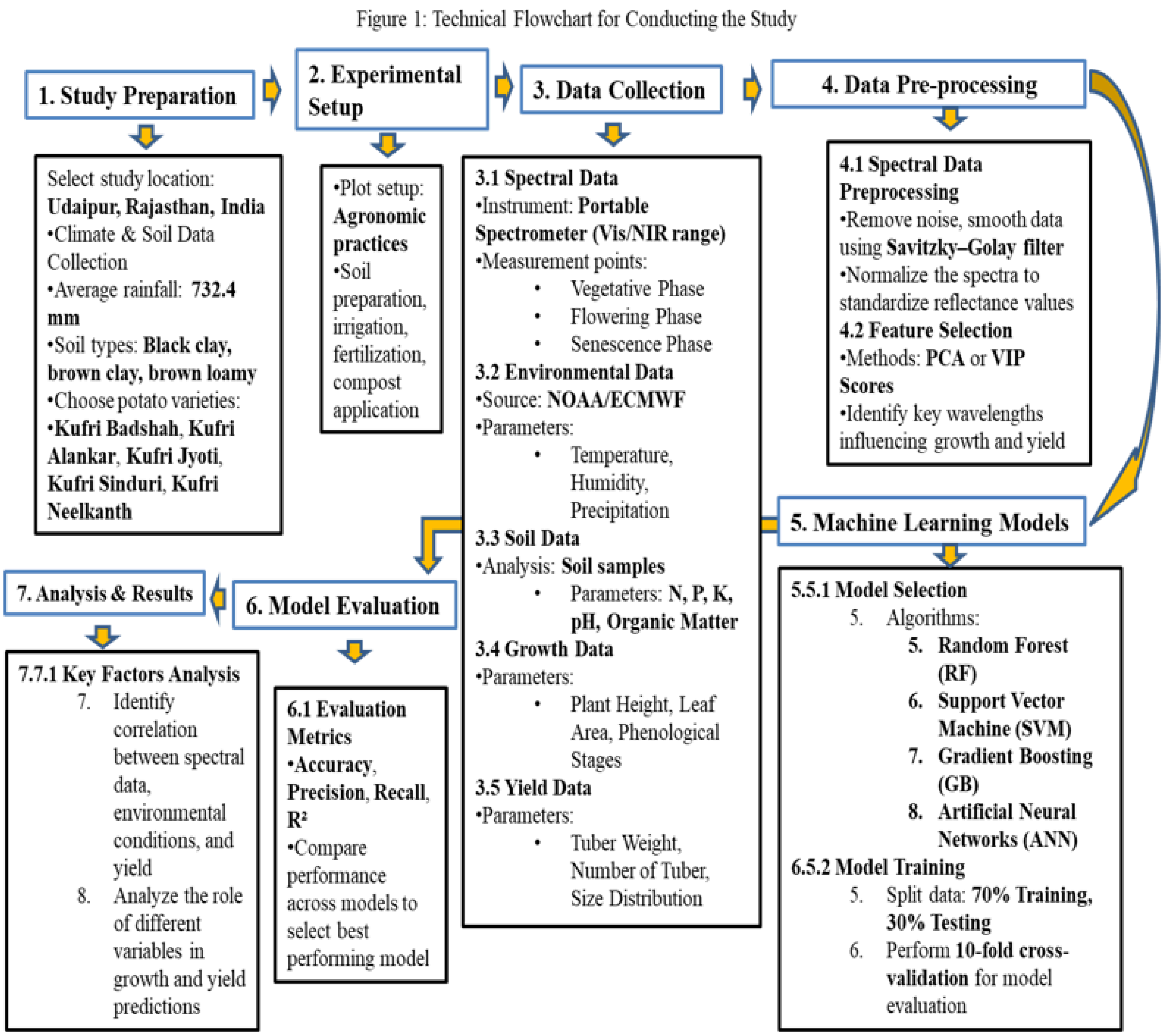

Figure 1

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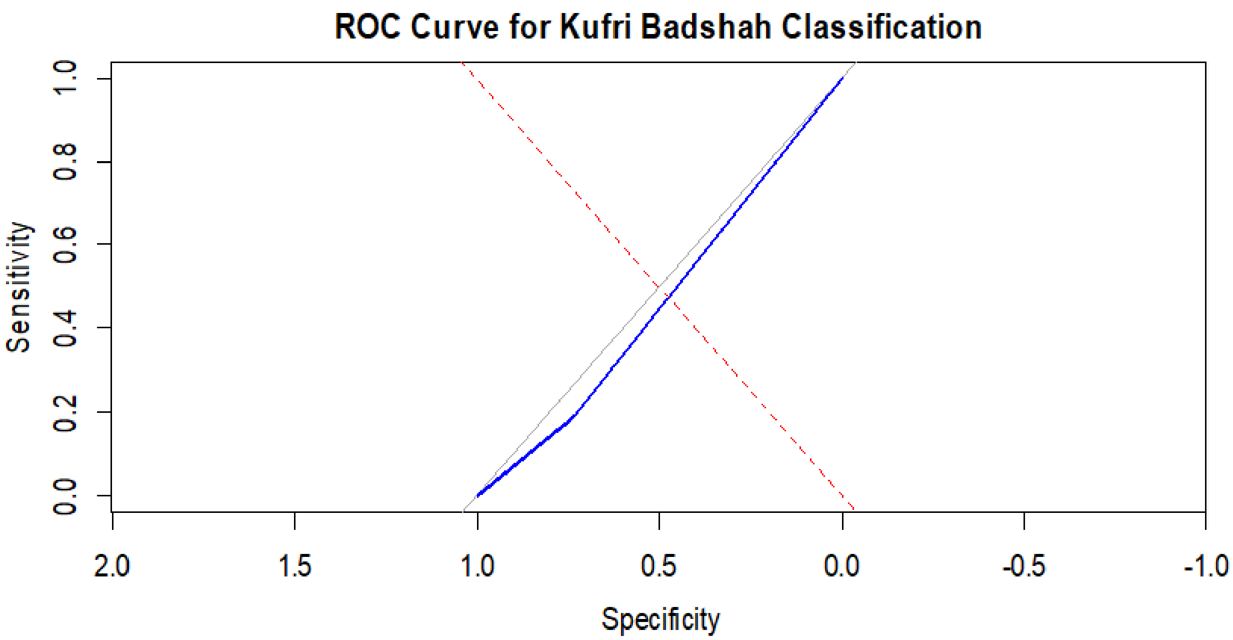

Figure 2

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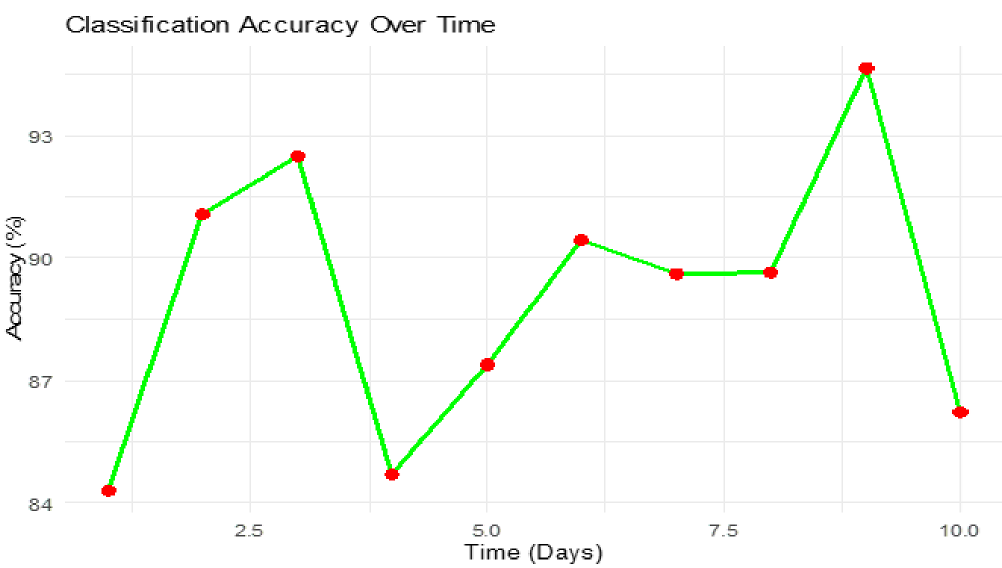

Figure 3

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