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Harnessing Digital Tools for NPK Deficiency Detection in Paddy Cultivation: ASurvey

Sharanamma M. Hugar
Research Scholar, Dept. of CSE, VTU CPGS RO kalaburagi, Affiliated to Visvesvaraya Technological University, Belagavi – 590018, INDIA

Dr. Mohammed Abdul Waheed
Professor, Department of CSE, VTU CPGS, RO, Kalaburagi., Affiliated to Visvesvaraya Technological University, Belagavi – 590018, INDIA

Abstract

Over the years, understanding the nutritional needs of agricultural plants has become paramount, especially concerning Nitrogen (N), Phosphorus (P), and Potassium (K) - commonly referred to as NPK. Deficiencies in these vital nutrients lead to significant agricultural and economic setbacks, given their crucial role in plant health and growth. In the past decade, techniques using image processing to diagnose NPK deficiencies and other nutritional imbalances in plants have emerged as an area of significant interest among researchers. Various methodologies have been developed for detecting, identifying, and quantifying these imbalances across a spectrum of crops. This article reviews pertinent research from 2007 to 2018, emphasizing advancements in the domain. The discussed studies employ criteria like image segmentation, feature extraction, feature selection, and classification. The article also underscores the current accomplishments and challenges in this field, providing insights and recommendations for future explorations related to diagnosing nutritional imbalances in agricultural plants.

Keywords: *Nutritional needs, Nitrogen (N), Phosphorus (P), Potassium (K), NPK Deficiency, Nutritional imbalances, Image Processing*

1 Introduction

Paddy, a staple for many, especially in rural regions, is the world's second most cultivated cereal. It hails from the Poaceae family and is primarily classified into two subspecies: Japonica and Indica. Known for its affordability and as a source of rice, paddy predominantly feeds the Asian continent once processed. However, like other agricultural plants, paddy is not exempt from the challenges of NPK deficiencies and other nutritional imbalances. According to the Food and Agriculture Organization of the United Nations (FAOSTAT), a staggering 91.05% of global paddy production is both grown and consumed by Asian countries [1]. The remaining production is distributed among other regions: 2.95% in Africa, 5.19% in America, 0.67% in Europe, and 0.15% in Oceania (refer to Fig. 1). Understanding and diagnosing these nutritional imbalances in paddy can significantly impact the quality and yield of this essential crop, which, when milled, provides rice for consumption.

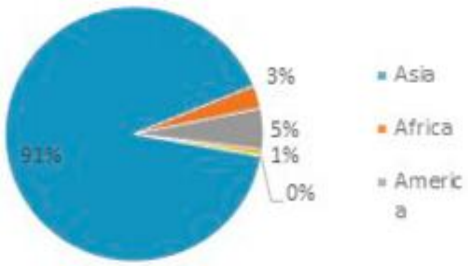

Figure. 1:-Production of Rice World (Source FAOSTAT)

According to data from the World Bank, there is a growing emphasis on the significance of paddy cultivation due to an anticipated surge in rice consumption. The demand for rice is projected to increase by a staggering 51% by 2025. Notably, this rise in consumption outpaces the projected growth rate of the global population. Fig. 2 visually represents this trend, showcasing the projection of rice consumption in major Asian countries from 1995 to 2015. As evident, the reliance on paddy as a primary source of rice will only intensify in the coming years, underscoring the importance of understanding and addressing nutritional imbalances such as NPK deficiencies.

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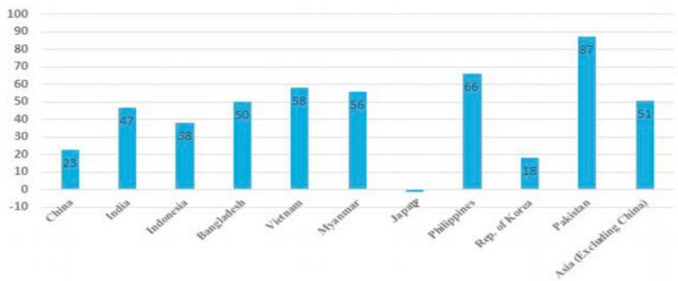

Figure. 2:-Projection of Rice Consumption in Percentage of Asian Countries, 1995-2025. (Source World Bank Population Projection, 1995-2025).

The demand for rice is anticipated to outpace production in many countries. Given this scenario, any damage to the rice crop is a major concern [2]. Historically, diagnosing rice plant diseases and gauging their severity was done through visual analysis, relying on experts' naked-eye observations. This approach, while valuable, is labor-intensive, costly, and challenging to implement over vast crop areas. With the burgeoning global population amplifying the demand for food, there's an urgent need to employ advanced technologies for timely and accurate disease detection and intervention.

Image processing techniques have emerged as a precise, cost-effective solution for identifying plant diseases. This paper offers a comprehensive review and comparison of these techniques, focusing on their applicability to plant disease diagnosis. It's worth noting that the rice crop's growth cycle encompasses four distinct phases:

Germination: The initial stage where the seed sprouts roots and shoots [4].

Vegetative Phase: Spanning from when the plant emerges from the ground until the panicle's initiation.

Reproductive Phase: This phase sees the panicle emerge from the tiller and continues until it's fully grown.

Ripening Phase: The panicle matures, ensuring the kernel within the grain has fully developed [3].

Diseases can strike at any stage, underscoring the importance of vigilant monitoring and early intervention.

2 Paddy Diseases and their Symptoms

Paddy diseases arise from various factors, including pathogens, insect pests, nutrient deficiencies, and abnormal environmental conditions [5]. These pathogens can be parasitic, bacterial, viral, or nematodal, damaging plant parts above and below the ground. This section details these paddy diseases, providing a visual guide to help understand the types of image processing and features required for their detection.

False Smut: Characterized by silvery-white structures that later resemble orange smoke or dust, False Smut infects developing panicles. The disease thrives in rainy and highly humid conditions and is common in lands with high nitrogen content [7].

Sheath Blight: Caused by the fungus Rhizoctonia solani Kuhn, this disease affects the straw of the rice plant. It manifests as initial lesions on leaf sheaths and the presence of sclerotia, affecting grains and underlying panicles [8].

Rice Blast: A major concern in parts of Gujarat, Rice Blast affects all aerial parts of the plant throughout its growth cycle. Symptoms range from seedling blight to leaf blasts and grain spots. The disease severely impacts crop growth, grain quality, and yield [8].

Leaf Scald: Presenting as narrow reddish-brown bands, sometimes lesions appear at leaf edges accompanied by yellow or golden borders [10].

Brown Spot: This disease manifests as round to oval dark brown lesions on rice plant leaves [10].

Bacterial Leaf Blight: Symptoms include elongated lesions on the leaf tip. These lesions, which can span several inches, transition from white to yellow due to bacterial effects [10].

Bakane: Affected rice plants exhibit abnormal elongation, particularly noticeable in the seedbed. These plants often remain in the growing stage, displaying empty panicles with yellow-tinted leaves. Other symptoms include reduced tillering, leaf drying, and the presence of partially filled, sterile, or empty grains [11].

3 Growth Phases of Paddy Crop and its Diseases

The rice crop undergoes a typical cultivation period of 3 to 6 months, progressing through several distinct growth phases: germination, vegetative, reproductive, and ripening.

Germination: This initial phase occurs before the emergence of the radicle and plumule from the seed. Once the embryo germinates, it evolves out of the seed, transitioning to what is recognized as a plantlet or seedling.

Vegetative: Following germination, the plant undergoes a vegetative growth phase, characterized by the development of its foundational structures.

Reproductive: In this phase, the plant focuses on reproducing, including panicle formation.

Ripening: This is the final phase, where the grains mature and the plant readies for harvest.

It's important to note that the rice crop is susceptible to various diseases at different stages of its growth. These diseases, corresponding to each growth stage, are detailed in Table 1.

Table 1:-Growth Phase of Rice with Diseases

Growth Phase of Rice	Diseases
Germination	Seed Rot
Vegetative Phase	Crown rotor foot rot (also known as Bakane),Leaf blast, Brown spot, Sheath blight,Leafscald,Leafsmut,StackburnorAlternarialeafspot,Whiteleafstreak,Whitetip,Bacterialleafblight,Crownsheathrot,Collar blast, Node blast
Reproductive and Ripening Phase	Rotten neck blast, Downy mildew, White ear head, Panicle blast, Bacterial panicle blight.

3.1 Adaptive Features of Paddy during the Germination Phase and Associated Dysfunctions

Germination is a critical phase for paddy and is influenced by various factors, including soil composition, microbial infections, and environmental conditions. Seed rot is a prevalent disease during this phase, predominantly caused by fungal pathogens. These fungi, particularly their spores (conidia), are often carried by rice seeds. As germination ensues, the fungus proliferates, resulting in weakened or dead seedlings.

Beyond these challenges, the seed quality chosen for germination plays a pivotal role. It's essential to use high-quality seeds for optimal growth. To ensure this, germination tests are indispensable [6]. These tests help measure seed quality and assist farmers in selecting the best seeds, setting the stage for successful cultivation. Fig. 3 depicts the germination process, highlighting it as a foundational phase in plant formation.

In contrast, Fig. 4 visually represents fungal infections observed in rice seeds. Ensuring that crops remain free from pathogens and optimizing plant efficiency are paramount. With the ever-growing global population, the demand for food continues to rise, making rice an essential staple in diets worldwide.

Figure. 3. Germination of Seed.

Figure. 4:- Fungal infected Rice seeds.

3.2 Vegetative Phase Diseases and Nutritional Imbalances in Rice Crop

During the vegetative phase, rice crops face multiple challenges from diseases caused by pathogens such as bacteria, fungi, and viruses. Some notable conditions affecting the yield in this phase include Crown rot (also known as Bakane or foot rot), Leaf smut, Stack burn (or Alternaria leaf spot), White leaf streak, White tip, Bacterial leaf blight, Crown sheath rot, Collar blast, and Node blast. Visual representations of these diseases can be found in Fig. 5.

In addition to diseases, mineral deficiencies significantly influence the growth and health of the rice crop. A balanced supply of essential macronutrients like potassium, magnesium, nitrogen, phosphorous, and zinc is vital for the optimal growth of the crop. Any deficiencies manifest primarily in the leaves, causing shape and color deformities. Fig. 6 showcases the visual effects of mineral deficiencies in rice plants, highlighting the impact of lacking essential nutrients such as nitrogen, potassium, magnesium, phosphorous, and zinc.

3.3 Reproductive and Ripening Phases: Disease Manifestations in Rice Crop

The rice crop's reproductive phase commences with the panicle's emergence from the stem, a stage called "Booting." This phase culminates when the panicle is fully visible, a stage called "Heading." Following this, the ripening phase ensues, marking the transformation of flowers into mature grains ready for harvest. This maturation process typically spans 15 to 40 days [12].

During these two critical growth phases, rice crops are susceptible to various diseases, including rotten neck blast, white ear head, panicle blast, and bacterial panicle blight. Fig. 7 visually illustrates these diseases, highlighting rice plants' challenges in the reproductive and ripening stages.

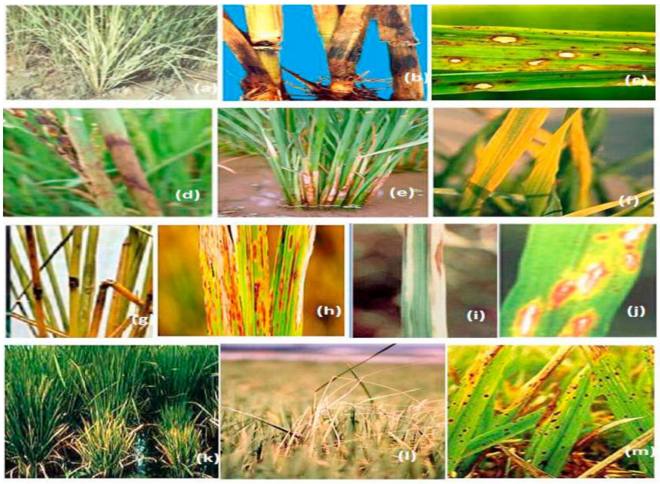

Figure. 5:-Different rice diseases in the vegetative phase (a) Yellow dwarf disease (b) stem rot (c) stack born (d) sheath rot (e) sheath blight (f) rice tungro (g) node blast (h) narrow brown spot (i) leaf blight (j) leaf blast (k) grassy stunt (l) foot rot (m) brown spot.

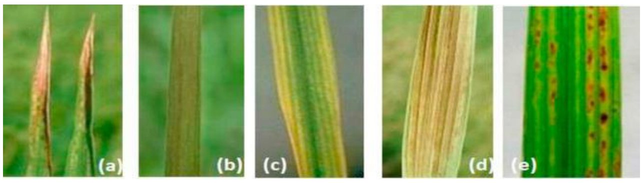

Figure. 6:-Mineral Deficiency in Rice Plant (a) Nitrogen (b) Potassium (c) Magnesium (d) Phosphorous (e) Zinc.

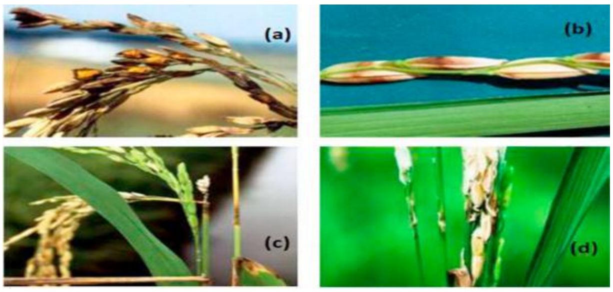

Figure. 7:-Different diseases in the reproductive and ripening phase (a) False Smut (b) Bacterial Panicle Blight (c) Rotten Neck Blast (d) Panicle Blast.

4 Role of Image Processing in Detecting and Identifying Paddy Diseases

Agriculture plays a pivotal role in the global economy. Unfortunately, many plants, including staple crops, fall victim to various fungal and bacterial diseases [13]. As the world's population grows, climatic changes exacerbate these plant diseases. One of the key challenges for sustainable agricultural development is reducing pesticide use to protect the environment and enhance crop quality. Implementing precise, accurate, and timely diagnostic methods can help decrease our reliance on pesticides.

Rice stands as a primary crop in countries like India. With technological advancements, there's a growing trend of leveraging these innovations for plant disease prediction. The fusion of image processing with data mining techniques offers several benefits, including:

- Identifying affected leaves and stems.

- Quantifying the impacted area.

- Delineating the shape of the infected region.

- Pinpointing the color variations in the affected areas.

Historically, manual classification and identification methods have been employed to detect different types of leaf diseases. These traditional methods, relying heavily on human input, are prone to errors. As a result, there's a pressing need to embrace advanced automated techniques, such as image processing and machine learning, to enhance the accuracy of paddy disease diagnosis.

The subsequent sections delve into the systematic steps of image processing. This includes a comparative analysis of image segmentation, feature extraction, feature selection, and classification techniques tailored for plant disease diagnosis. Furthermore, the sections highlight the recent successes in this domain and discuss prevailing limitations.

4.1 Image Acquisition

Image acquisition serves as the foundational step in image processing, providing insights into the origins of digital images. Beyond simply capturing an image, this phase often encompasses pre-processing tasks like image scaling. However, obtaining high-quality images is not without its challenges [14]. Proper equipment, like a high-quality scanner or a camera with a good resolution, is essential to ensure that the images acquired are suitable for further processing and analysis.

4.2 Image Pre-Processing

Image processing involves transforming an input image into a digital format to enhance its quality or extract valuable information. Essentially, it's a form of signal processing where the input is an image, such as a video frame or photograph, and the output can be an altered image or specific features associated with the original image [15]. Key tasks in image pre-processing include filtering, color conversion, and detail enhancement [16]. Recent research focusing on image pre-processing techniques specific to paddy disease diagnosis is summarized in Table 2.

Table 2:-Comparative Analysis of Different Techniques Applied in the Pre-Processing Stage.

Reference	Year	Objective	Methodology	Parametric Measure	Result
[17]	2018	Noise Reduction	Gaussian Filtering	Accuracy	98.63%
[18]	2017	Detection of plant disease over cottonplant	Machine Learning Regression-Median Filtering	Accuracy	83.26%
[19]	2017	Detection of infected and healthy leaf	Image processing-Weiner filtering	Accuracy	80-99%
[20]	2017	Automated crop disease identification	HSV color extraction	Accuracy	Sensitivity= 98.91% Precision= 99.04%
[21]	2017	Diagnosing plant disease	Gaussian smooth approach	Accuracy	90.96%

4.3 Segmentation

Image processing is pivotal in diagnosing deficiencies and diseases in paddy plants. Through transforming and analyzing images, it's possible to identify areas of concern in crops, including the vital N, P, and K (Nitrogen, Phosphorus, and Potassium) deficiencies. Segmenting images to focus on specific components or areas of interest remains one of the most challenging yet crucial tasks in digital image processing. Some of the Segmentation Techniques:

Fuzzy C Mean: This method allows each datum partial membership in clusters. It's particularly effective in distinguishing between healthy and deficient regions of a leaf based on color variations, which are vital for diagnosing mineral imbalances like NPK deficiency [22].

K-Means Clustering: This approach involves choosing initial centers or pixels from an affected leaf, representing healthy and deficient regions. Given the characteristic color changes associated with such deficiencies, it's particularly adept at identifying clusters with mineral deficiencies [22].

Thresholding: A basic segmentation technique, thresholding utilizes values obtained from the histogram of the input dataset. It's particularly useful for straightforward images but may not be ideal for more complex images where mineral deficiencies manifest subtly.

Many researchers have recently embraced various segmentation techniques for diagnosing paddy diseases, including mineral deficiencies. Their findings are summarized in Table 3

Table 3:-Comparative Analysis of Different Segmentation Techniques for Plant Disease Diagnosis.

Reference	Year	Objective	Methodology	Parametric Measure
[22]	2017	Identification of mineral deficiency	Fuzzy C mean and K- Mean Clustering	Accuracy (FCM)= 92%, Accuracy(K-Mean)=85%
[23]	2017	Cucumber leaf spot disease detection	Fuzzy C means	Average segmentation error=0.12% and exhibited an efficiency accuracy in the detection of the disease
[24]	2012	Segmentation of leaves	K-mean clustering	Higher accuracy rate
[25]	2009	Diagnosis of paddy disease	Variable, Global, And Automatic Threshold Based On Otsu Method	Accuracy= 87.5%
[26]	2012	Classification of rice plant dysfunctions	segmentation by Otsu method	Accuracy= 78%
[27]	2015	Detection and classification of plant diseases	Image processing	Higher accuracy
[28]	2018	Rice leaf blast detection	Color image thresholding	The severity of the disease is adequately classified.

4.4 Feature Extraction

The successful classification of images, especially in identifying NPK deficiencies in paddy plants, heavily relies on the effectiveness of feature extraction techniques. Features act as the key parameters that guide and influence the classification process.

Texture Extraction: A vital component in image processing, texture extraction identifies patterns or arrangements in the structure of an image. The significance of texture data makes this extraction pivotal, especially in applications such as remote sensing and biomedical imaging, where detailed texture patterns, like those seen in mineral deficiencies, need to be discerned [29].

Color Extraction: Color variations can indicate specific deficiencies, making color extraction crucial. While pixels in digital images are typically represented in RGB space, other models like HIS and CIE are frequently utilized for their advantages in segmentation processes. Color changes can signal nutrient imbalances, like NPK deficiencies, in paddy plants [30].

Shape Extraction: Basic descriptors such as object count, image area, and dimensions are crucial to describe the shape and structure of an image. These features are particularly useful in detecting deformities or abnormalities in shape caused by mineral deficiencies [32].

Edge Detection: Edge detection identifies areas of brightness discontinuity for discerning boundaries and delineations within an image. This method is invaluable in image segmentation and can help detect boundaries of affected regions in paddy leaves [33].

In conclusion, feature extraction techniques are invaluable in diagnosing paddy crops' NPK and other mineral deficiencies. As agricultural demands grow, harnessing these advanced image-processing methodologies will be vital for sustainable and efficient farming.

Table 4:-Comparative Analysis of Different Feature Extraction Techniques for Plant Disease Diagnosis.

Reference	Year	Objective	Methodology	Result
[29]	2007	Texture Extraction	Image Processing	Accuracy= 88.56%
[30]	2013	Detecting unhealthy leaf portion	Texture feature	Accuracy= 94%
[31]	2018	Evaluation of soybean leaf defoliation	Color Extraction	Accuracy= 96%
[32]	2017	Identification of infected leaf	Image extraction-leaf color	Higher accuracy

4.5 Classification

Classification systems in agricultural image processing are pivotal for diagnosing plant diseases, particularly for rice plants. These systems can analyze and classify diseases using captured images based on distinctive features. Classification methodologies can be broadly categorized into supervised and unsupervised techniques. While supervised classification relies on known sets of pixels, unsupervised classification banks on properties inherent in pixels, creating clusters without prior training. Here's a synopsis of significant classification techniques:

Support Vector Machine (SVM): A robust classifier, SVM determines the decision boundary between two classes as a separating hyper-plane. This hyper-plane strives to distinguish between two types, ensuring optimal separation [36].

Probabilistic Neural Network (PNN): Rooted in the Bayesian classification statistical approach, PNN is a feed-forward neural network encompassing input, hidden, and output layers. The hidden layer, known as the pattern layer, predominantly contains Bayesian classifiers. PNN leverages non-parametric estimators to obtain multivariate probability density functions, proving especially effective for detecting rice leaves affected by diseases like rice leaf roller [38].

Convolutional Neural Network (CNN): An unsupervised deep learning model, CNN learns through filters operating in the image domain. Inspired by the biological vision system, CNN combines the principles of organic vision and neural systems. Although training a CNN demands considerable time, its classification accuracy is commendable [40].

In summary, advanced classification techniques have revolutionized how rice plant diseases are detected and diagnosed, offering promising avenues for future research and practical applications in agriculture

Table 5:-Comparative Analysis of Different Classification Techniques for Plant Disease Diagnosis.

Reference	Year	Objective	Methodology	Parametric Measure	Result
[34]	2012	Leaf disease detection	Color extraction	Accuracy	Disease spot accurately Detected.
[35]	2017	Detect the classification of leaf disease	K-Mean Clustering	Accuracy	FCM=95% K-Mean=85.05%
[36]	2009	Detection of rice seed disease	Support Vector Machine	Accuracy	97.2%
[37]	2015	Identification of rice panicle	Principal Component Analysis and Support Vector Machine	Accuracy • Raw Reflectance Spectra • First Reflectance Spectra • Second Reflectance Spectra	 96.55% 99.14% 96.55%
[38]	2018	Rice disease determination	Principal Component Analysis and Neural network	Accuracy of BP neural network	95.83%
[39]	2014	Detection of rice plant disease	Back Propagation And Artificial Neural Network	Accuracy	100%

5 Findings and Future Direction for Diagnosis of Paddy Diseases

This manuscript reviews various methods that utilize machine learning and image processing techniques to detect and categorize NPK deficiencies in paddy leaves and panicles. Our survey shows that most research focuses on diagnosing leaf-based NPK imbalances in paddy using a common framework illustrated in Fig.8. Here are some suggestions to further improve the current state-of-the-art.

5.1 Real-time Application Development

Existing solutions for detecting NPK deficiencies in paddy primarily rely on offline images, with very few achieving satisfactory accuracy in real-world scenarios. While a handful of web portals and mobile applications (e.g., Leaf Doctor, Leaf Coder, atLeaf+) offer online guidance, their coverage of paddy's NPK deficiencies remains limited. There's a pressing need to create mobile and web platforms capable of instantly predicting NPK imbalances using real-time images.

5.2 Evaluating Recent Techniques

Over the past decade, research has primarily focused on diagnosing leaf-based NPK deficiencies in paddy, often limited to a few types. Notably, there's a gap in addressing imbalances in other parts of the rice plant, such as panicles and stems. Huang, S. et al. (2015) [41] remains one of the few who investigated panicle-based deficiencies using hyperspectral imaging. Additionally, while Bhakta I. et al. (2018) [42] utilized thermal imaging to detect bacterial blight, the high costs of hyperspectral and thermal imaging devices limit their widespread adoption. Furthermore, the adoption of convolutional neural networks (CNN), as highlighted by Lu. Y. et al. (2017) [40] offer promising accuracy but introduce computational and memory challenges.

If new imaging devices and learning techniques aren't accessible to the public in a user-friendly manner, their practicality becomes questionable. A potential solution could be developing a fully automated system tailored for mobile and web platforms, ensuring ease of use while addressing NPK deficiencies.

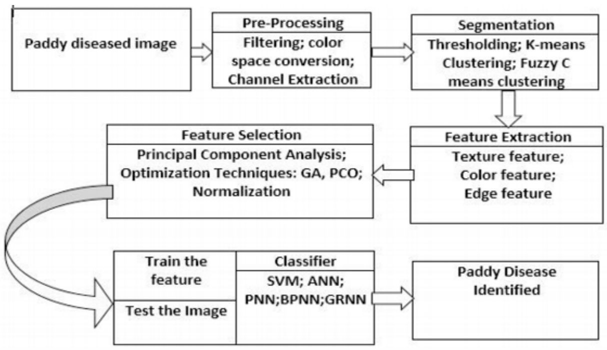

Figure. 8:-Suggested Framework for Paddy Deficiencies Diagnosis.

6 Conclusion

This paper offers a comprehensive review of studies from 2007 to 2018, concentrating on the NPK deficiencies in paddy and their relation to various growth stages. The survey aims to aid researchers in understanding the intricate dynamics of Nitrogen (N), Phosphorus (P), and Potassium (K) deficiencies in paddy crops.

Furthermore, the paper elucidates various image-processing techniques for diagnosing these deficiencies, encompassing pre-processing, segmentation, feature extraction, feature selection, and classification. The challenges of diagnosing NPK imbalances in paddy are also discussed, with the paper proposing a universally accepted framework.

Advanced imaging systems, such as hyperspectral and thermal imaging, are highlighted. The success of these systems is intrinsically linked to the quality of images, the volume of training data, and the features of the samples under study. Any shortcomings in the setup can directly influence the results. Moreover, employing Convolutional Neural Networks (CNN) necessitates advanced infrastructure, both in terms of computation and memory. An intriguing solution might be the fusion of expert system methodologies with computer vision and machine learning techniques. Crafting such a system could pave the way for breakthroughs in addressing NPK deficiencies in paddy.

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