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Research Article

ARTIFICIAL INTELLIGENCE BASED SUSTAINABLE COTTON CROP PRODUCTION USING REMOTE SENSING DATASET

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Abstract

The decline in cotton production in Pakistan has directly impacted the country's foreign exchange earnings, plummeting from twelve million bales in 1991, the number decreased to four million bales in 2020. Considering a substantial portion of Pakistan's exports are linked to the textiles area, with 40% of jobs tied to production, this decline is concerning. Factors such as climate change and changes in biotic and abiotic stresses have contributed to substantial losses in cotton production. In Pakistan, where 90% of farmers face resource constraints, there is a pressing need for more accurate mechanisms to understand the challenges in crop production. Timely acknowledgment and adoption of more flexible approaches to irrigation, fertilizer application, and pest and disease control are crucial. Excessive use of pesticides has exacerbated the situation, leading to the development of resistance among pests and diseases. Traditional visual inspection methods alone are insufficient for predicting crop health effectively, resulting in deprived crop yields and financial losses for agrarians. Enhancing crop health condition requires leveraging information gathered from remote sensing and terrestrial sensors, along with truth field surveys. By processing this data through tools like the Decision Support System for Agrotechnology Transfer (DSSAT) and employing machine learning techniques such as artificial neural networks, more accurate local and field-level advice can be provided to farmers. This approach aims to optimize crop management practices, reduce losses, and ultimately improve farmers' incomes.

Keywords: Remote sensing, pests and disease, climate change, Sustainable cotton production, input applications, and smart advisory.
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1. INTRODUCTION

Remote sensing is a fundamental concept that encompasses various agricultural equipment procedures. In this application, each sensing device is interconnected through remote connections, operating autonomously without human intervention (Stephen Leo et al., 2020). These sensing devices transmit data across the network to control agricultural processes. Fundamentally, remote sensing is like a satellite-based computational network that can serve farms and agricultural industry. By means of this process, the gap between machines and any humans/remote systems will be bridged through the embedded computing into a distributed system (Balkarishna G et al., 2019). Primarily, it is aimed at ensuring that all the agricultural field devices are connected at all times (Dan Li et al., 2019). Remote sensing has the power to do monitoring, controlling, information acquisition, algorithms, and output identification. It gives opportunities for studying agriculture practices using remote sensing data (Salman Qadri et al. 2019). The use of remote sensing is gaining momentum both at the global and agricultural level (Aslam, Tanveer et al., 2021). Remote sensing devices have been widely adopted by different countries and in agricultural areas, aiming for connection and collaboration. The Internet of Things (IoT) is a gaming application that is transforming multifarious aspects of our day-to-day lives, including agriculture, smart home automation, and food supply (Steve Schriber et al., 2021). The technology of Wireless Sensor Networks (WSN) is the critical factor in such application, which is the simplest framework of wireless networks and autonomous mechanisms created for the detection and analysis of environmental and physical factors (Rajasekaran Thangarasu et al., 2019).

As IoT expands in the digital realm, any object within a distributed system can transform into a remote-sensing device (USDA, 2021). WSNs and Radio Frequency Identification (RFID) technology have emerged as remarkably efficient tools and devices within this framework. Figure 1 illustrates the drawbacks associated with pesticides.

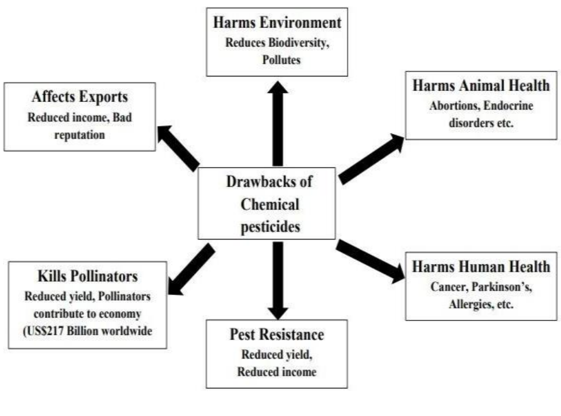

Figure 1: Drawback of Pesticides

Many farmers and growers possess a deep understanding of agriculture but often rely on conventional farming methods and traditional processes. However, thanks a lot to innovations in remote sensing and appliance technology, the agricultural divisions in emerging countries are experiencing growth in IoT applications (Cranfield University, 2021). This shift is significant because many growers and farmers encounter various losses in agriculture, often stemming from poor quality and management practices within the sector.

The agricultural sector faces several challenges, including:

1. Inefficient management of irrigation.
2. Insufficient water systems.
3. Pest infections.
4. Lack of proper harvesting knowledge.
5. Inadequate utilization of machinery.

Agricultural products constitute a significant source of income for any country (Dhivya Elavarasan et al., 2020). Among the major crops worldwide is "white gold," or cotton, with Pakistan being a prominent producer. However, the agricultural sector in Pakistan experiences substantial losses annually due to poor cultivation methods and attacks by diseases and insects (Muhammad Arshad et al., 2009). In 2018, the agricultural sector encountered a 38% crop loss due to various diseases and insect infestations. An example of an insect is depicted in Figure 2.

Figure 2: Different insects of attack in Cotton

Various diseases caused by rodents, bacteria, and fungi significantly impact crop cultivation processes. Fluctuations in temperature and humidity during sowing further complicate crop development. Effective crop development relies on timely interventions such as spraying, fertilization, and pesticide use, as highlighted by Wajad Nazeer et al. (2023). Continuous monitoring is essential for successful crop cultivation. Many farmers and growers are embracing the latest agricultural technologies and practices. However, they also rely on the wisdom and experience of older farmers for guidance, as noted by Shuja Abbas (2020). Such expertise is crucial for providing timely advice and support when needed. In Pakistan, various crops such as vegetables, fruits, and cotton are cultivated. Utilizing remote sensing, which is a leading-edge machine learning program in which we are going to be tackling the agricultural challenges, is exactly the way we are going to handle this issue. The system employs a data collection and analysis approach to offer optimal options regarding problems encountered in agriculture. Remote sensing devices are one of the important instruments for profiling the given problems and giving recommendations to eliminate the identified problems.

Staff working with remote sensing devices do all the data collection and produce various outcomes of great importance. Data from the sensors is subsequently sent through the network to the growers' instruments or cell phones. With this strategy of observation, the farmer has a perfect chance of taking a panoramic view of the farmland and this makes the process simple and reliable. Since it acts as an effective way to shield crops from pests or fungus. Remote sensing is, therefore, applied in crop cultivation to promote the fast growth of crop farmers and also group maintenance.

This study outlines a straightforward framework comprising:

1. Crop management system
2. Weather alert system
3. Control of insect attacks
4. Management of pesticide and fertilizer usage

2. EXPERT ARCHITECTURE IN REMOTE SENSING

We aim to optimize a practical remote sensing architecture to address various agricultural field-related issues. The following components are utilized for improved solutions:

1. Installation of sensor devices in agricultural fields.
2. Examination and analysis of soil humidity and leaf wetness.
3. Measurement of climate temperature using installed sensors.
4. Utilization of remote sensing devices to collect data and transmit it for optimal solutions.

2.1. Sensor Device Development

Data collection from environmental distances is one of the remote sensing devices that is used to get data from various relevant fields, such as climate change, soil moisture, and humidity. Without these devices, agricultural crop systems would have to depend on totally manual management since, according to J. E. Bergez et al. (2010), the devices come in handy for control. The architecture of these devices involves advanced components like a super microprocessor and a 2-gigabyte microSD card.

Each board comprises four groups of remote sensing appliances: humidity sensors, soil sensors, climate temperature sensors, and leaf sensors. The synchronization of these devices and running them jointly helps the production of exact results. These machines sparingly use huge distances of around 600 meters. The framework of the remote network can be seen in Figure 3.

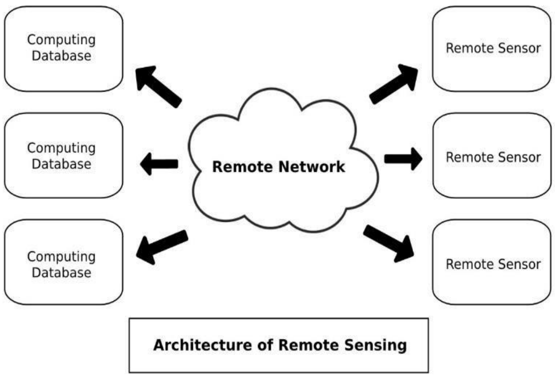

Figure 3: Framework of Remote Network

2.2. Implementation of Solutions for Farmers

The server acts as the data provider, offering information to farmers by selecting devices such as email or smartphones. A mobile app is specifically designed for the convenience of farmers. Through this app, farmers will receive alerts and notifications about dangerous situations like weather changes or pest epidemics. This app will serve as a valued tool, empowering farmers with real-time information to enhance agricultural productivity and efficiency.

2.3. Proposed Efficient Solution

Our proposed solutions prioritize cost-effective devices, avoiding the need for expensive equipment. Farmers typically allocate budgets for seeds, fertilizers, and pesticides. By integrating these devices into their practices, farmers can save money while still achieving successful crop production. We have successfully implemented these solutions in crop production, reducing farmers' costs and enhancing crop yields.

Investing in remote sensing technology may initially require a one-time expense. However, the benefits are significant. For instance, in cotton cultivation, continuous monitoring is enabled through cameras and sensing devices, providing round-the-clock surveillance.

3. RESULTS CATEGORIZATION AND DISCUSSION

The best first search (BFS) Algorithm, implemented within WEKA, was utilized to achieve optimal results and accuracy. Three key features were employed to ensure precise results: Texture features, Histogram features, and Binary features. These features were selected to enhance the performance of machine learning classifiers in experimental processes conducted on cotton digital-image data, denoted as V-1 to V-4, as illustrated in Table 1.

Table 1: Field Image Datasets of Cotton

Cotton Varieties	**No of Classes**	**No of Images**
Verity-1	V-1	100
Verity-2	V-2	100
Verity-3	V-3	100
Verity-4	V-4	100

Various machine learning methods have been used to classify various characteristics of different types of cotton. The experimental results for these techniques are defined in Table (2,4,6).

3.1. Tree Classifiers

In the initial stages of this practical study, tree classifiers such as Tree J-48 and Random Tree were utilized. Tree J-48 achieved an overall accuracy of 95.2084%, outperforming Random Tree, which achieved an accuracy of 92.874%. These results are presented in Table 2.

3.2. Meta Classifiers

Meta-ML classifiers were implemented to enhance the accuracy of the results. It was observed that the Meta classifier exhibited superior accuracy compared to tree-based classifiers. Specifically, Meta-classification through Regression achieved an improved precision of 97.5834% compared to meta-bagging, which achieved an accuracy of 96.374%. These results are presented in Table 4.

Table 2: Tree-Based Classification Output Datasets

Tree Classification	**Kappa Statistic**	**MAE**	**T P Rate**	**RMS E**	**ROC**	**F P Rate**	**T N I**	**Time in (Second)**	**Final Output**
J-48	0.9629	0.0173	0.973	0.1166	0.984	0.008	2401	0.15	95.2084%
RANDOM - TREE	0.944	0.0207	0.958	0.1437	0.974	0.015	2401	0.04	92.874%

Table 3: Confusion-Matrix Table for Tree J-48

No of Classes	**V-1**	**V-2**	**V-3**	**V-4**
V-1	580	7	4	9
V-2	7	590	2	1
V-3	12	4	570	13
V-4	7	1	10	582

3.3. Confusion Matrix Table

The confusion matrix table of the Meta meta-classification through the Regression classifier depicts the maximum values that are arranged diagonally, as shown in Table 5.

3.4. Comparative Graph of Machine Learning Classifiers

Based on the provided details, the general accuracy results of various machine learning classifiers exist in the following sequence: Function SMO, Multi-Layer Perception, Random Tree, Meta Classifier through Regression, Meta Bagging, and J-48 Tree.

Among these classifiers, Multi-Layer Perception attained the highest accuracy result of 99.83334% with respect to all other classifiers. This formation of accuracy results from extreme to lowest is illustrated in Figure 5.

total weight. In the third step, the owner checks the moisture, and if it is too high, there is a cut from the total weight of 144 kg. If a dispute arises between the broker and the farmer, all bags are already marked, so the broker returns all the stock to the farmer.

Most daal factories have their own logistics and transport facilities. The factory receives orders and supplies Daal to the wholesaler according to their demand. Wholesalers pay the price of transportation, with the cost varying based on the type of pulses transported. With the above data, it was possible to carry out a financial analysis of mung beans as shown in Table 5

Table 4: Meta Classifier Performance Dataset

Meta Classification	Kappa Statistic	M A E	T P Rate	RMSE	ROC	F P Rate	T N I	Time in (Second)	Final Output
Classification Through Regression	0.9812	0.0338	0.987	0.0972	0.998	0.006	2400	0.53	97.5834%
Bagging	0.964	0.0277	0.976	0.0992	0.997	0.008	2400	0.48	96.374%

Table 5: Confusion Table for Meta Classification Using Regression Algorithm

No of Classes	V-1	V-2	V-3	V-4
V-1	587	4	6	5
V-2	6	589	4	1
V-3	4	2	594	2
V-4	5	1	2	594

3.5. Processor

The quality of pulses at the Daal factory is assessed rigorously. The broker brings the product to the factory worker, who takes a random sample of 10 kg from the 220-240 bags (1 bag=40 kg) loaded on the truck. First, they use a sieve to check the waste in the sample and weigh that waste. If the waste is 200 grams from that sample, it becomes 2 kg for 100 kg, and this is used to calculate the overall waste in the load. In the second step, a few grams of grains are taken from the sample, all grains are counted, and the whitish, broken, blackish, and discolour grains are separated and counted. If the broken or discoloured grains exceed 3% of the total seed count, then the owner/farmers bear a ‘charge’ of 77 kg for each percent above 3% deducted from the

Based on the provided details, the complete accuracy results of multiple ML classifiers exist in the following sequence: Meta Classifier through Regression, Meta Bagging, J48 Tree, and Random Tree. Among these classifiers, Classification through Regression achieved the highest accuracy result of 98.58% with respect to other classifiers. This formation of accuracy results from extreme to smallest is illustrated in Figure 5.

4. CONCLUSION

The farm guidance system aims to deliver concise and accurate information to farmers by leveraging artificial intelligence. It was observed that if farmers would be able to use state of the art technology, then a better cotton crop will be produced. This Decision Support System for Agrotechnology

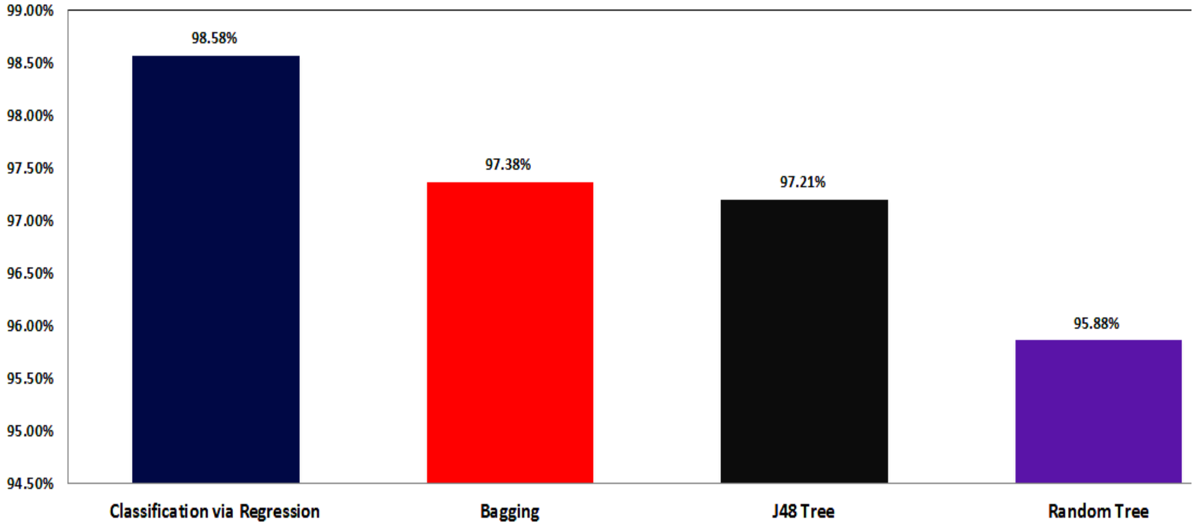

Figure 4: Graphical Comparison of Multiple ML Classifiers' Performance

Transfer (DSSAT) and employing machine learning techniques such as artificial neural networks, more accurate local and field-level advice can be provided to farmers, this approach holds promise for enhancing future predictions, ultimately leading to improved crop production and management practices.

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