Effective crop categorization using wavelet transform based optimized long short-term memory technique

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ABSTRACT

Effective crop categorization is important for keeping track of how crops grow and how much they produce in the future. Gathering crop data on categories, regions, and space distribution in a timely and accurate way could give a scientifically sound reason for changes to the way crops are organized. Polarimetric synthetic aperture radar dataset provides sufficient information for accurate crop categorization. It is essential to classify crops in order to successfully. This article presents wavelet transform (WT) based optimizedlong short-term memory (LSTM) deep learning (DL) for effective crop categorization. Image denoising is performed by WT. Denoising algorithms for images attempt to find a middle ground between totally removing all of the image's noise and preserving essential, signal-free components of the picture in their original state. After denoising of images, crop image classification is achieved by LSTM and support vector machine (SVM) algorithm. LSTM has achieved 99.5% accuracy.

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1. INTRODUCTION

Crop categorisation is a crucial element of remote sensing monitoring in agricultural environments [1]. This categorisation is crucial for future crop development and productivity assessment. Changes to agricultural organisation may be substantiated by scientific evidence if timely and accurate data on crop types, geographic areas, and spatial distribution is collected. Crop categorisation is essential for optimising agricultural production, allocating farming resources effectively, and safeguarding the nation's food supply [2].

The majority of individuals engage in little activity, since agriculture relies on the maintenance of stationary plant species. Agriculture yields several products, including food, raw materials, textiles, and economic freedom [3]. India's agricultural industry, which ranks second globally, has significant challenges with irrigation, fertilisation, and crop rotation. Crops have undergone continuous development by farmers from the beginning of agriculture. Identifying plants with advantageous characteristics, such as pest or drought resistance, is a current research goal. The growing urban population is adversely correlated with the availability of water resources. Environmental issues, including soil deterioration and inadequate irrigation, exacerbate the complex challenges confronting the agricultural sector [4]. Climate change may modify both the average temperature and the frequency and pattern of precipitation. Each of these modifications impacts agriculture in a distinct way.

These experiments use advanced information technology and internet connectivity to collect, assess, and analyse vast amounts of agricultural data. This data collection includes information about weather, soil conditions, market demands, and land utilization [5]. The purpose of these experiments is to provide farmers with more data to facilitate improved and more profitable decisions. An increasing number of researchers have focused on agricultural decision support systems in recent years [6].

Artificial intelligence (AI) may be used in real time to assist farmers in making educated decisions by enabling computer algorithms to provide valuable recommendations and insights. To assist farmers in making better decisions, this may be implemented. Although other systems are analogous to an agricultural decision support system (ADSS), it does not provide farmers with clear guidance. ADSS may assist decision-makers in enhancing future endeavours while also providing options for existing operations. The final decision rests with the farmers, resulting in this outcome [7].

The techniques used in image analysis are very successful in distinguishing between images and their components. This development of the field enables bioinformatics, document identification, medical imaging, biometric identification, and several other practical uses. A range of reviews offers an extensive study of several image analysis methodologies. Implementing photo analysis inside an automated system is a challenging endeavour [8]. Assume, for the sake of discussion, that X is an image of a tissue section including several cell types. The objective of an image analysis approach may be confined to identifying the cells due to the presence of several other observable components. The predominant image classification algorithms are categorised into two main classes: clustering-based methods and conventional machine learning techniques. Algorithms for grouping and classification based on machine learning are associated with the characteristics of handmade items, whereas deep learning (DL) methods autonomously extract the properties of handcrafted works [9].

Swarms consist of several homogeneous units that engage in local communication and interaction without a centralised hierarchy or external regulation. Consequently, new global behavioural patterns may emerge [10]. There are many insects in their natural habitat. In response to the shortcomings of previous optimisation strategies, researchers in the late 1970s devised heuristic and metaheuristic optimisation methods. Unlike traditional approaches, such as non-linearity, these advanced techniques effectively addressed dynamic issues. An instance of this issue was a non-linear connection [11]. Additional characteristics include robustness, discontinuity, discreteness, global performance, multi-objectivity, unpredictability, and efficacy [12]. Machines may get advantages from machine learning similarly to how people assimilate new knowledge and enhance their previous experiences [13]. Precision agriculture significantly depends on machine learning, which benefits farmers and opens new research opportunities [14].

This article presents wavelet transform (WT) based optimizedlong short-term memory (LSTM) DL for effective crop categorization. Image denoising is performed by WT. Denoising algorithms for images attempt to find a middle ground between totally removing all of the image's noise and preserving essential, signal-free components of the picture in their original state. After denoising of images, crop image classification is achieved by LSTM and support vector machine (SVM) algorithm. LSTM has achieved 99.5% accuracy.

2. LITERATURE SURVEY

It is essential to provide an image in a matrix style for the computer to comprehend the picture. This is a list including both real numbers and integers. picture processing encompasses the digitisation of a picture and the subsequent use of several techniques to enhance its overall quality. Noise is a sort of information that may be eliminated from a picture since it is unnecessary for its interpretation. Images are processed for several purposes, including data extraction, object visualisation, image restoration, data retrieval, measurement, object identification, and image measurement. Image processing is essential in several fields, including medicine, forensics, materials science, the military, the film and video game sectors, and weather forecasting, in addition to agriculture.

Following the 1990s, self-training computers using training datasets supplanted expert systems, resulting in a significant improvement in the accuracy of these computers' illness diagnosis capabilities, particularly for life-threatening conditions. The purpose of the pre-processing step of picture creation is to enhance image legibility by applying suitable procedures and transforming it into a format comprehensible to a computer. Examples of preprocessing techniques include picture enhancement, median filtering, colourspace transformation, scaling, noise reduction, thresholding, and histogram equalisation. The subsequent stages of segmentation, feature selection, and classification are significantly enhanced by the use of superior images. At this stage, alterations to the histogram, including contrast stretching for enhanced clarity, and noise reduction techniques are implemented. The histogram is advantageous for photographs since it discloses information about the image itself, which is quite valuable.

Fegraus *et al.* [15] are developing a decision-support system for the agriculture and ecosystem of Tanzania. The procedure involves consolidating information from many sources, including but not limited to geographic information systems (GIS), remote sensing imagery, field-collected data, and plot surveys. The device belonging to the user is designated as the client device. JavaScript and asynchronous JavaScript and XML (AJAX) are used to regulate the behaviour of the functional components engaged in service access via the dashboard. Entities that interact using the representational state transfer application programming interface (REST API). It is an astute tool for decision-making that synthesises complex facts into a clear conclusion comprehensible to everybody. The charts, graphs, and tables used to present graphs, maps, and other kinds of geographical data may assume several formats, although their complexity remains constrained. The implementation of this dashboard system, sometimes referred to as a knowledge transfer tool, was advantageous by supplying essential information to farmers. This management plan includes the formulation of recommendations for climate, soil nutrients, vegetation mapping, environmental sustainability, water availability, and water quality.

Chetty and Adewumi [16] examined a solution to the challenge of fairly allocating limited agricultural land among several seasonal crops. Precision agriculture involves careful planning of harvests to optimise yields from a particular parcel of land by adjusting resource allocations seasonally. This may be achieved using agricultural technology, including global positioning system (GPS) and satellite imaging. Recent developments in swarm intelligence including the cuckoo search, the firefly algorithm, and glowworm swarm optimisation. All of them have shown superiority over the genetic algorithm regarding the quality of the solutions produced. Recent advancements in the subject include glowworm swarm optimisation. A mathematical model is developed to address issues with South Africa's current irrigation systems, which is then applied to single-crop, double-crop, and triple-crop scenarios, respectively. In determining hectare allocations, the crops considered included cotton, groundnuts, and reduced maize hectare allocations.

Kassim and Abdullah [17] developed an ontology-based method within the domain of agricultural guidance systems. The software architecture for the decision making process was designed explicitly to enable the distribution of this information to agricultural producers. The only constraints are users, an information module, and a database of information. Judging crop productivity is challenging due to the multitude of real-time elements influencing these choices. Numerous real-time factors are beyond the farmer's control or even estimation, including the soil's physical qualities and meteorological conditions. Adjusting some elements may be necessary before we can attain our objective of maximising profits. The counsel offered by agricultural professionals in reports or other static sources may not be suitable for all new and young farmers, regardless of their farm's location or the farmers' individual features. This advisory system establishes a fundamental framework for collaboration and information exchange, essential for identifying a dynamic solution appropriate for the prevailing soil, vegetation, and other variables.

In their proposal, Shouyi *et al.* [18] provide a comprehensive system for precision agriculture including both hardware and software components. Information is collected, processed, and used for decision-making using a network of multimedia and wireless sensors. In this scenario, a wireless sensor network is used to gather data on the surrounding environment, including temperature, soil moisture, sun radiation, rainfall, soil composition, and humidity. Factors pertinent to agriculture that are observed and used in many ways to enhance agricultural output. To effectively forecast yields and strategically use pesticides, it is essential to regulate the quantity of fertiliser applied and to monitor plant metrics like as growth, disease incidence, and pest insect presence. The primary emphasis was on data collection using the predominant methods of remote sensing, executed on a large scale. This method, referred to as the precision agriculture sensing system, operates autonomously without human involvement. A solitary node including sensors integrated onto a single chip was accountable for the production of a substantial volume of data. This node was able to perceive scalar information and multimedia data. The sensor nodes in the network were equipped with a durable battery backup capable of sustaining them throughout their lifespans, facilitated by a battery array switching mechanism. This technique is now used to enhance agricultural productivity at forty distinct locations in China.

Numerous farmers already use multi-cropping, believing it will help meet the increasing need for agricultural output, Gray *et al.* [19] assert that precise observation is essential for predicting crop yields. They relied on moderate resolution imaging spectroradiometer (MODIS) sensors, which had excellent temporal resolution but limited spatial resolution, due to the inadequacy of the available static data. It is now possible to maximise the benefits derived from crop cultivation. This technology is an enhancement of previous remote sensing techniques and has been used to optimally map the intensity of multicropping throughout Asia. The enhanced version of the application can accommodate more than two cropping cycles annually, address complications stemming from the convergence of actual and arbitrary calendars, and manage absent data. The gathered information serves purposes beyond only generating output estimates and agricultural strategies. An example of this is the risk assessment presented by Zhang *et al*. [20].

Crop failure is often due to natural disasters such as droughts, floods, and windstorms. This method is also applicable to many circumstances. The federal government has implemented several measures in response to the loss, including offering crop insurance, disaster relief funds, and agricultural investment portfolios. This may serve as proof for a grant or loan application requiring verification of money distribution for infrastructure comparable to the requested amount. This instance uses yield history to assess the likelihood of crop failure. This research only detailed the risk assessment technique grounded in the cause of loss, rather than the traditional yield-based method. The trial findings demonstrate that the proposed strategy is effective. Academics not only provide answers to issues via proposed cures, but they also assess the related risks. Sangbuapuan [21] identified Thailand's rice cultivation as a key focus for its information and communications technology (ICT) strategy. The Thai government has aggressively pushed this resource to facilitate data gathering and information exchange in the field. The availability of this resource has substantially improved farmers' ability to adapt to changing conditions and make informed choices. The Thai government is vigorously promoting community rice centres, which include infrastructure tailored to certain crops and regions, including computer labs and irrigation systems. Community rice centresare situated across Thailand.

3. METHOD

This section presents WT based optimized LSTM DL for effective crop categorization (Figure 1). Image denoising is performed by WT. Denoising algorithms for images attempt to find a middle ground between totally removing all of the image's noise and preserving essential, signal-free components of the picture in their original state. After denoising of images, crop image classification is achieved by LSTM and SVM algorithm. LSTM has achieved 99.5% accuracy.

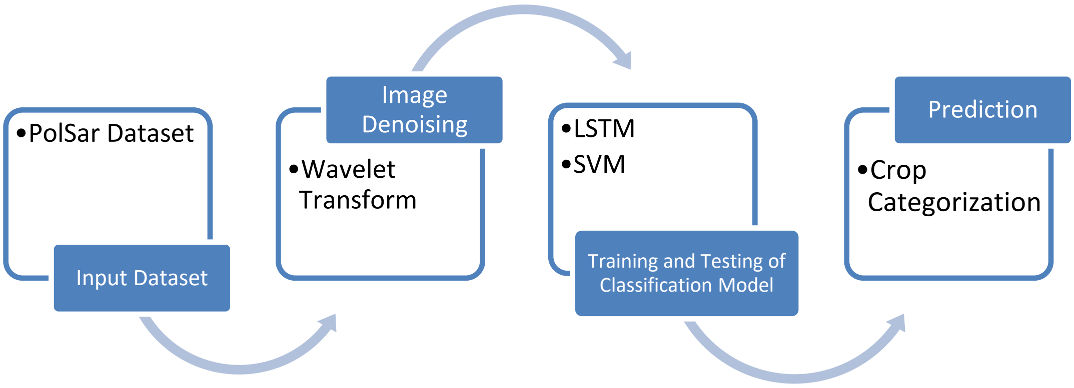


Figure 1. WT based optimized LSTM DL for effective crop categorization

Denoising algorithms for images attempt to find a middle ground between totally removing all of the image's noise and preserving essential, signal-free components of the picture in their original state. Therefore, in order to achieve optimal performance, it is necessary to take into consideration the spatial properties of the processed and noisy image. The WT [22] has established itself as a common method for denoising and compressing pictures due to the various beneficial qualities that it has. Because of the strong decorrelation that the WT creates between neighbouring pixels, the spatial and frequency domains may now be localised independently of one another. Using the subbands that are made feasible by this method, an image may have its high and low frequency components neatly separated from one another. Image enhancement and restoration are two applications that may make advantage of the many wavelet-based approaches that have been developed. When processing an image, each wavelet coefficient is compared to a threshold. If the coefficient is lower than the threshold, it is set to zero; if it is bigger than the threshold, it is either maintained or its magnitude is somewhat decreased. The thresholding process is the foundation of the fundamental wavelet image restoration techniques. This is where it all begins. Due to the fact that the WT is effective at energy compression, it is common for small wavelet coefficients to be attributable to noise, whereas large wavelet coefficients are typically associated with important picture characteristics, such as edges. As a result, this strategy follows naturally and intuitively from the fact that the WT is capable of efficiently compacting energy.

The LSTM [23] design is shown in Figure 2, and it is constructed by linking critical components that are referred to as memory blocks. Data is stored in memory cells that are coupled to one another by self-feedback connections, and a specialised logic gate located inside the memory block is responsible for controlling the flow of data. A well-structured memory cell is responsible for regulating the flow of input and stores data as well as an activation function. Memory cells store data. In a similar manner, the activation function and the regulating cell are both used by the output gate in order to control the flow of data. Gates are used to govern the flow of information into and out of the block, as well as at the point of output and any moment the data is ready to be forgotten. Gates may also be employed at any point in time when the data is ready to be forgotten. To save the data for longer time duration, it should be saved and accessed by thegates with multiplicative nature. Sigmoid function (0-1) along with this nature of gates helping the LSTM to store or erase the data into cell state.

The SVM [24] is by far the most popular supervised machine learning model that may be used for either classification (which provides a discrete class) or regression (which gives a continuous value). Despite the fact that it may also be used for regression, its strongest use is in the classification issue. The analysis of sentiment was used by a great number of publications before this one. SVM has been employed by the top performers on even the most well-known SemEval-tasks. The fundamental purpose of a SVM is to generate a hyperplane in N-dimensional space that may be used to partition a dataset into separate groups. A decision boundary that helps to clearly separate the space that is inhabited by data points may be conceptualised as a hyperplane, which can be understood as serving this purpose. It searches for a hyperplane that is located at the greatest feasible distance from the components of each class that are located closest to it. The locations that are closest to the hyperplane are referred to as support vectors. The support vectors have an effect on the hyperplane, both in terms of its direction and its position. The optimal hyperplane may be found as soon as the margin reaches its highest possible value. Figure 3 displays this particular SVM model. SVMs have as its principal purpose the widening of the distance between different classes by the production of sharp hyperplanes (decision boundary). In situations when there are just two dimensions at play, the decision boundary, also known as the hyperplane, is a straight line. If there are three features, or dimensions, then the hyperplane can only be two dimensional. Whenever there are more than three characteristics being considered, it will employ a hyperplane as the decision boundary.

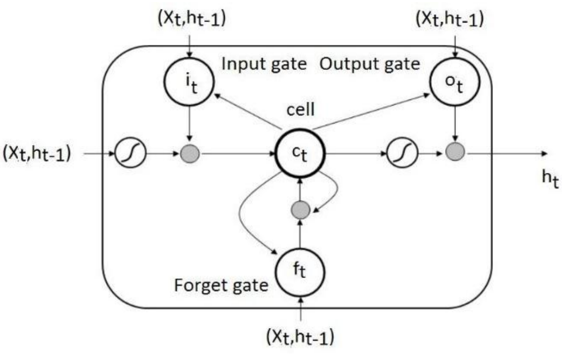


Figure 2. LSTM internal gate connections

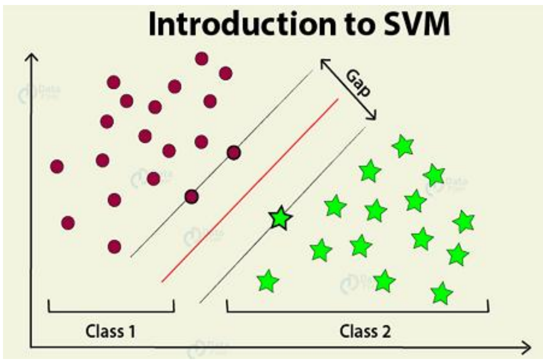


Figure 3. SVM model working

4. RESULT AND DISCUSSION

Polarimetric synthetic aperture radar (PolSar) dataset [25] provides sufficient information for accurate crop categorization. This dataset consists of crop related images of different regions and different crops. These images help in crop classification in accurate manner. It is essential to classify crops in order to successfully guide agricultural production, effectively distribute farming resources, and guarantee the safety of the nation’s food supply. In this experimental work, 250 images of PolSar dataset are used. These 250 images cover 6 crop categories. 200 images are used to train the classification model and remaining 50 images are used to test the classification model.

- Accuracy: the proportion of all predictions that are predicted correctly (accurately) is referred to as accuracy.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$

- Sensitivity: the proportion of positive cases projected as positive is known as sensitivity. It's also known as 'recall.'

$$Sensitivity = (TP) / (TP + FN)$$

- Specificity: the proportion of actual negative cases projected as negative is known as sensitivity.

$$Specificity = (TN) / (TN + FP)$$

- False discovery rate: the proportion of actual negative cases projected as positive is known as false discovery rate. It's also known as 'false positive rate'.

$$FalseDiscoveryRate = (FP) / (TN + FP)$$

The sum of the false discovery rate and the specificity is 1.

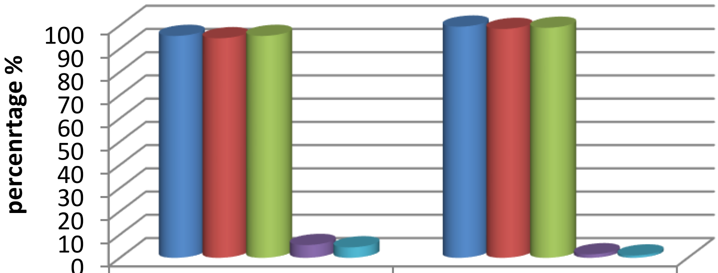
- False omission rate: the proportion of positive cases projected as negative is known as false discovery rate. It's also known as 'false negative rate'.

$$FalseOmissionRate = (FN) / (TP + FN)$$

The sum of the false omission rate and sensitivity is 1.

The predominant criterion for assessing a classifier's performance is accuracy, defined as the ratio of correct classifications produced. This metric allows for the comparison of the available classifiers. Although evaluating classifier fairness is essential, other factors are often overlooked. A diverse array of potential results exists when evaluating a specific population or dataset related to a condition. A true negative (TN), a false positive (FP), a true positive (TP), or any combination thereof may occur. Maintaining objectivity is essential while assessing the classifier's performance, and the aforementioned measures will significantly assist in this endeavour.

Results are shown in Figure 4. Accuracy of WT based LSTM is 99.5%. It is higher than the accuracy of WT based SVM. Similarly, sensitivity, specificity, false omission rate, false discovery rate of WT enabled LSTM is better than WT based SVM. LSTM is achieving better results across all parameters for crop categorization.



	WT SVM	WT LSTM
Accuracy	95.5	99.5
Sensitivity	94.5	98.5
Specificity	95.5	99
False Omission Rate	5.5	1.5
False Discovery Rate	4.5	1

Deep Learning Methods

Figure 4. Crop classification-accuracy, sensitivity, specificity, false discovery rate, and false omission rate

5. CONCLUSION

Monitoring agricultural settings using remote sensing requires a number of different steps, one of which is the categorization of crops. This sorting is vital for keeping track of how crops develop and how much they yield in the future, thus it is very important that it be done. The timely and precise collection of agricultural data on categories, regions, and space distribution might provide a scientifically valid justification for modifications to the way crops are structured. The information included in the dataset generated by polarimetric synthetic aperture radar is adequate for accurate crop classification. It is vital to categorise crops so that agricultural output may be successfully guided, farming resources can be properly distributed, and the nation’s food supply can be ensured to be safe. Image denoising is achieved through WT. Denoising algorithms for photos aim to find a medium ground between completely eliminating all of the image’s noise and retaining critical, signal-free components of the picture in their original condition. This may be thought of as a compromise between the two extremes described above. Following the process of denoising the pictures, the LSTM and SVM algorithms are used to classify the cropped images. The LSTM algorithm has attained an accuracy of 99.5%. LSTM is vital DL method for accurately classifying the crops images.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review &**E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

Ethical approval was not required for this study, as it did not involve human or animal subjects.

DATA AVAILABILITY

The data that support the findings of this study are openly available in [https://github.com/liuxuvip/PolSF] at reference number [25].

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