Protecting Agricultural Crops from Locusts - Using Machine Learning Tools and Techniques

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Abstract- In the aftermath of severe rains, it is usual for locust outbreaks to begin well away from human settlements. In light of the pressing need to undertake such surveys, unmanned aerial vehicles (UAVs), often known as drones, have been proposed as a potential means of scanning areas and discovering major locust concentrations. UAVs are small aircraft that fly through the air and collect data. Swarms can be prevented from developing and migrating to feed on large areas of crops by employing this method to determine where sprays should be applied as soon as possible after they have been formed and travelling. This review provides a quantitative overview of machine learning (ML) applications and research in locust management, focuses on these applications and research in locust management. We believe this is because the concepts of locust control and related notions in image processing hold a great deal of promise.

Indexed Terms- Agricultural Crops, Locusts, Machine Learning, Deep Learning

I. INTRODUCTION

Pests such as the locust and the grasshopper have been wreaking havoc on crops and endangering human lives for millennia, and their devastation has been documented in both ancient and contemporary literature [1–4]. The gregarious phase of pest locusts and grasshoppers, during which they can move large distances and inflict severe damage to crops, pastures, and other green plants [5,6], is particularly dangerous. Locusts have a unique advantage over other insects in terms of colony growth because of their quick expansion. During the solitaire period, locusts play an important part in the ecology of the environment. Land management has an impact on the dynamics of locust populations as well [7, 8]. If the reader is interested in locust phase polyphenism and population density studies, they should refer to [8–11].

One of the most damaging species, the desert locust (Schistocerca gregaria), has been responsible for devastating outbreaks and plagues in the twentieth and twenty-first centuries [4,12]. When the desert locust is at its lowest density, it can be found at low densities in a 16 million km^2 range spanning from Africa to Asia [13]. In areas [14], the desert locust breeds sequentially as it migrates downwind [15]. A further example is the rapid invasion of Moroccan locusts in Sardinia, Italy, during the summers of 2019 and 2020, which caused hundreds of hectares of crop damage [16-18]. A number of large-scale and small outbreaks of distinct locust species around the world have demonstrated that locust pests constitute a threat to food security, as well as the devastation caused by their presence and the importance of good locust management services.

Infestations can be long-term (e.g., grasshopper infestations in Africa Sahel and grasshopper/locust outbreaks in China) or cyclical (e.g., plague locust and desert locust infestations in Australia)[4]. Locust outbreaks have a negative influence on a variety of areas, including food security, land management, and natural environment. These range from the complete loss of grazing crops and fields to the negative consequences of insecticides used to combat the infestation, among other things. The short-to long-term consequences of crop damage and chemical contamination as a result of control measurements are particularly detrimental [4, 19].

II. LOCUST MONITORING SYSTEM

Plant protection professionals collect data on locust kinds, instars, and populations in the field for conventional locust monitoring systems, which are then used to identify the insects. As a result of these constraints, several researchers [17,18] have increased their monitoring scales. The monitoring of individual locusts and locust populations is now done on a regional scale rather than on a quadrat scale, as was formerly done. In order to compensate for the shortcomings of conventional approaches [19-23], these researchers have turned to observation technologies for assistance. Several outstanding findings have been reported by multiple researchers [22] as a result of their efforts.

Bryceson and Wright [23] showed simulation model on locust breeding is able to efficiently substitute missing ground survey data, which was first proposed by Bryceson and Wright in 1986 and first implemented in 1989. According to Bryceson et al. [24], data was used to identify semi-arid areas in southwest Queensland as likely hotspot locations for outbreaks of the Australian plague locust.

Desert locusts in dry and semi-arid habitats are being monitored daily by Waldner et al. [25], who created a colorimetric translation from spot-vegetation and moderate resolution imaging spectroradiometer data that helps in monitoring. This method is considered to be accurate in breeding locations, it was found to be less accurate when used in winter breeding areas.
According to the research team [25], the spatial resolution is coarse for fragmented patterns. As a result of their findings, they devised a random forest approach based on landscape membership for assessing the hydrological regime and locust structure. The moisture present in the soil is used by Gómez et al. [26] for extracting the temperature, soil moisture, leaf area, root zones in order to investigate their correlations with desert locust species occurrences. When dealing with the locust pandemic, it is not enough to merely build new satellite remote sensing monitoring tools to keep track of the situation on the ground. Because of interference from orbits and weather, it is hard for remote sensing satellites to match the timeliness and duration requirements of surveillance, which are imposed by these systems.

If satellite remote sensing technology is to be used to monitor and issue warnings for locust plague outbreaks, it must be able to recognise the relationship between the density of locusts and the structural changes associated with the locust by observing vegetation and hydrothermal growth conditions at different locations. To accomplish this, a large volume of locust observation data at the quadrat-scale is required. To fully comprehend the mechanics of locust plague incidence and the driving variables that cause them, observational data from a small number of locust colonies is also required. As a result, developing rapid and accurate sample-scale locust information collection systems is critical for understanding the causes and processes of locust [27] and offering accurate and timely warnings.

A significant benefit of computer vision techniques, which have improved rapidly in recent years [28-31], has been the improvement in insect monitoring and identification. Using scale-invariant feature [32], locust were all identified with high accuracy. In the case of pests, Cai et al. [33] used eigenvalues from leaves nibbled by pests to detect eigenvalues and then used backpropagation (BP) neural networks to construct an identification model.

Zhang [34] classified pests using neural network classifier, and the results showed that the classifier was 85.70% accurate. An image processing technique that dynamically extracts colour, area, and morphological information from photos was used to identify locusts, and population densities were calculated using this technique. When identifying locusts, Xiong et al. [36] used near-infrared spectroscopy and hierarchical clustering to build a model that they called the Xiong model. This method is used for the rapid detection of locusts in complex ecosystems with interwoven plant life, mud layers, and rocks. They calculated the accuracy of this model to be 91.67%.

The researchers at Chen et al. [37] employed deep learning in conjunction with other techniques like feature learning and classification to develop a pest identification system that was able to recognise 16 different species of common pests. The recognizability accuracy of the modelled approach was tested in light traps and varied from 66.00 to

90.00% in natural circumstances. According to Thenmozhi et al. [38], CNN model (Table 1) was developed using three publicly accessible insect datasets and attained accuracy rates of 96.75%, 97.47%, and 95.97%, respectively. Most of these investigations were concerned largely with obtaining various types of insect counts, which was the primary goal for the bulk of these investigations. It is uncommon to see field experiments on the automatic identification of locust types and stages in their various stages.

Table 1: Locust Management System

Model	Accuracy
AlexNet	73.68%
ResNet18	67.60%
GoogLeNet	69.12%
ResNet50	80.84%
VggNet	80.70%

III. IMPORTANCE LOCATING THE INFESTATIONS OF LOCUST

Other countries, such as China and Argentina, have effectively implemented locust prevention strategies. By knowing when and where infestations are most common, it has become easier to locate localised infestations in such a large area. As a result of the use of a decision support system (DSS) in locust management, forecasters, operations, and field personnel are able to make better decisions about when and where they should conduct surveys and deploy control measures.

The DSS is based on an open plains habitat map that is computer-based and contains layers of data. A rudimentary map can be updated for the most recent locust outbreaks, as well as past outbreaks dating back to 1970. Wetness distributions in this region can be derived from Bureau of Meteorology interpolations. There is more importance placed on whether or not the rainfall is sufficient to keep the grass green and the locusts alive than on the amount of rainfall itself. For grass response, 40 mm of rain is required in central Queensland for grass response. However, 25 mm of rain is sufficient in south-west Queensland where rain drains off from the rocky areas onto neighbouring grassy depressions.

During the two months it takes locusts to complete their life cycle in the summer, long-lasting grasses such as Aristida and Astrebla species remain green in both regions [39, 40]. It has been replaced by improved pastures or crops, and two big rainfall events are necessary for each generation of locusts in the temperate agricultural zone regularly invaded by locusts [41]. The DSS takes these distinctions into account since they are crucial for the simulation of growth and survival.

The optimal time of year to conduct a survey to find huge populations of locusts depends on the development of locusts after rain. Before accurate projections of spring hatching could be established, particularly in the subtropical interior areas of the Australian plague locust, more detailed research was needed [42]. It was shown that a greater developmental temperature threshold was to blame for the embryonic diapause. By autumn, the temperature barrier for stage IVc (approximately 45% of development) has risen from 16 degrees Celsius to as high as 26–32 degrees Celsius.

Instead of using ambient temperature as in conventional day-degree models, DSS locust development models use day-degrees of locust body temperature. Models for locusts incorporate body temperatures since locusts can bask and boost their body temperatures by 10–15 degrees Celsius over ambient [43]. This data is useful because surveys are carried out at times and places where locusts are most likely to be present. Many infestations are discovered by landowners after they have been reported, despite the fact that models can help predict some infestations. The early detection of small locust infestations requires regular contact with landowners who will alert authorities if they observe the pests.

For early intervention to be effective, accurate data cannot be acquired quickly enough. To conduct surveys, field workers can travel across state lines without restriction. Every day, survey data is entered onto palmtop computers and emailed to headquarters, where it is analysed. Our data quality and timeliness are unmatched by any other pest management company. It is possible to use the DSS to prioritise survey and control activities in eastern Australia for headquarters staff to use. The highly-trained field base officers in charge of their region collaborate to make decisions on control actions. If the locust population is manageable, field officers move immediately to build a temporary control base. Because of the devolution of authority to regional employees, control activities can begin as soon as locusts are spotted.

IV. VARIOUS LOCUST CONTROL TECHNIQUES

It was not a long before Symmons had a major impact on how we control our systems. The New South Wales Department of Agriculture (NSWDA) implemented undiluted chemical aerial spraying [44]. It has become increasingly vital for the APLC to employ ULV sprays in the parched interior, where water is scarce. Apply water-based sprays early in the morning, and space them at least 25–30 metres apart. If there is a light to moderate breeze, the APLC has developed ULV spraying techniques that allow spraying at intervals of 50–100 m, with the spraying continuing throughout the day if there is sufficient breeze [45] [46]. The use of wider track spacings and continuous spraying throughout the day enabled preventive control.

Landowners and aircraft ULV spraying were utilised in New South Wales agriculture to reduce nymphal bands and prevent large, dense adult swarms, particularly those that were close to trees [44]. Nymphal populations were quickly reduced by APLC aircraft, especially in densely packed bands that could be seen from the air. In order to ensure that a considerable number of adults were treated, the minimum density for swarm control was reduced from high density (50–100/m2) to medium density (10–30/m2). Low density swarms (4–10/m2) require treatment on occasion in order to achieve efficient preventive control in the interior. Other important considerations are limiting the impact on the environment and the economy. The APLC is now creating an environmental management system (EMS) to reduce these costs and demonstrate accountability to stakeholders and other interested parties. The application of pesticides in the field necessitates substantial training for field workers to minimise operator health and safety hazards and environmental impacts.

The results of this study can be used to apply appropriate actions when adverse effects in invertebrates and vertebrates are detected. Pesticide application has been transformed thanks to the widespread adoption of spray planes outfitted with DGPS devices. Sprays are guided by the DGPS to ensure that the least amount of pesticide is applied exactly where it is needed. Environmental and consumer costs have been reduced by using the lowest effective dose for locust control. It is possible that within a few days, nymphal bands that had previously been in areas where the insecticide was not applied will march into sprayed areas and pick up deadly amounts of the poison and perish. Because only a small portion of the target area is actually sprayed, aircraft spray duration and pesticide use are greatly reduced.

Due to the anticipated future restrictions on chemicals, a biological insecticide was predicted to become increasingly important in their place. The Locust and grasshopper biocontrol committee (LGBC) was formed in 1997 to commercialise Metarhizium for locust control after the fungus was shown to be so promising in the field of scientific research. In 2000, this locust biopesticide was used to treat over 25 000 hectares of locust bands in the world for the first time in practise. Metarhizium was found to be particularly beneficial in the treatment of environmentally sensitive areas, organic properties, and areas where landowners were going to put their animals or products on the market. Because of the increased demand for organic beef in Asian markets, it is becoming increasingly difficult to control the locust source areas in western Queensland and northern South Australia with only insecticides.

V. STUDIES ON LOCUSTS OUTBREAK AND PREDICTION OF HATCHING

Researchers in this area are interested in predicting locust outbreaks or the commencement of egg-laying. Even while prior measurements, historical data, and monitoring are an important part of this research, the focus here is on the future instead of the past, as it was previously.

While population dynamics are still important for locust outbreak prediction, Rosenberg [50] says that changes in precipitation and vegetation can now be used to detect swarming and plague activity. Long-term forecasts based on historical data, climate, pest frequencies and estimated anomalies; short-term forecasts of up to three months are based on the combination of these elements. Using the FAO SWARMS, researchers can perform large-scale analyses of the entire desert locust distribution area, for example. Short-term forecasts are handled nationally using the Ramses system, which allows for comparisons between the current month and the prior year and between the current month and the previous year [50].

An introduction to GIS-based operational forecasting and monitoring of desert locusts can be found in Healey et al. [51]. Using remote sensing to collect weather and habitat data will be increasingly important in the future, say the scientists. Burt et al. [52,113] recommended using Meteosat IR data for the estimation of rainfall using the temperature on cloud and enhance the forecasting process for Senegalese grasshopper outbreaks in the early season. Even if we employ this strategy, it is probable that the Senegalese grasshopper will hatch in 2–3 weeks.
According to a study conducted by Todd et al. [54], climate variability can affect brown locust outbreaks in southern Africa. There was a correlation between brown locust infestations and La Nina events, as well as increased December rainfall. According to the study conclusions, models that incorporate high-frequency variability and climate indices have a lot of opportunity for improvement.

Ceccato et al. [55] studied the desert locust that focused on the conditions that allowed the outbreak to take place. According to the researchers, rainfall estimates were used to predict the possibility of future desert locust outbreaks. For their research, they examined the early warning system for desert locusts and evaluated the potential of novel climate prediction methodologies to help predict desert locust growth and mobility.

According to IRI projections for desert locust development, environmental factors can be correctly predicted in order to lengthen response times for additional reactions and prepare for management operations if necessary. A long-term forecast of rainfall is needed in order to accurately predict a locust outbreak. Ceccato et al. [56] were unable to accurately anticipate seasonal rainfall in North Africa because of the unexpected frequency and intensity of midlatitude storms. Rainfall forecasts [57] can be more accurate when oceanic conditions in the atmospheric circulation change more slowly.

Piou et al. [58] employed a prediction approach in Mauritania desert locust habitat, combining historical field survey data with NDVI data to predict future locust populations. Savitzky-Golay filtering of the NDVI time series was used to smooth the data, and a total of 27 vegetation metrics were produced prior to the date of observation. Prior to conducting a field investigation, NDVI values were calculated for a range of different time intervals to prepare for the study. The researchers used a logistic regression model to see how well each metric was linked to the positions of the ground control points they were testing on. They discovered that NDVI changes that occurred between 32 and 48 days before a locust infestation were the most accurate predictors of an infestation. Following the findings, it is possible to forecast the existence of locusts during remission times by looking at measures that indicate vegetative change in the environment.

Piou et al. [58] discovered a relationship between the quantity of mean vegetation and the locust at the local scale, even when geomorphological variables were not taken into account. Topographical features, on the other hand, were responsible for determining the greatest NDVI. Therefore, Piou et al. [58] propose that the development of a locust population is linked to the development of vegetation; they also assert that rainfall; and they conclude that better locust management, according to the authors, requires technologies that translate normalised difference vegetation index (NDVI) data into predictive presence-absence maps.

As a result of the research conducted by Tronin et al. [59], the locust hazard index (LHI) for the Italian locust has been established and applied. The LHI worked admirably in both instances and, as a result, may be used as a forecasting tool in the future. Taking this into consideration, Tronin et al. [59] developed a threshold for LHI to assess the outbreaks in the Siberian research area. When it came to European research, LHI, on the other hand, was a complete failure. To assess the accuracy of the forecasts, researchers in both locations looked at false alarms and epidemics that had gone unnoticed. It was determined that LHI failed to perform effectively with regards to its size and the variety of landscapes, biomes, and climatic variables that it contains.

According to Veran et al. [60], the geographic and temporal locust dynamics can be modelled using MODIS data in order to predict the varying proportions of woody and herbaceous plants in a given location. Over much of eastern Australia, rainfall and land cover variables appear to be the most efficient predictors of outbreak geographic variability. According to their findings, the researchers concluded that hierarchical spatial models can be used to improve the prediction of locust outbreaks in the future. When Zheng et al. [61] developed a forecast model for the Chinese province of Xinjiang, they used geographic information systems (GIS) to incorporate monthly average temperatures, relative humidity, elevations, slopes, NDVI and PH data. According to the findings of the study, adults and nymphs have a different relationship with the NDVI index. The best prediction performance was achieved by nymphs ($R2 = 0.461$), demonstrating how dependent this life stage is on the surrounding environmental conditions [62].

In addition to rainfall and vegetation, soil moisture must also be taken into consideration while formulating locust projections. Crooks and Cheke [63] explored the suitability of C-band SAR data for soil moisture retrieval in brown locust life cycle modelling, rather than depending on rainfall estimations for soil moisture retrieval. It will be crucial in the development of SAR images to collect data on a large enough scale and in a timely manner in order to forecast the weather.

It has been modelled by Meynard et al. [64] that climate change scenarios could alter the geographic distributions of locust subspecies, resulting in ecological niche changes between desert locust subspecies from the South and North. With the use of a variety of SDMs and climate parameters, the scientists arrived at the conclusion that there was significant niche conservatism between the two subspecies studied.

During the course of their research, Piou et al. [65] investigated how the presence of desert locusts in recession areas affected the growth of the normalised difference vegetation index, rainfall, and land surface temperature. When each component is examined separately, as the authors did, desert locust occurrence can be explained and predicted using statistical analysis of each variable.

VI. DAMAGE AND LOSS ASSESSMENT STUDIES

In comparison to healthy vegetation, stressed or wounded vegetation has lower reflectance. Due to a decrease in chlorophyll, plants that are getting stressed are detected using edge spectrum and can be distinguished from healthy plants. There is a considerable decline in green vegetation in both the VI and high-resolution SAR images, respectively. In China, studies on damage assessment have mostly focused on migratory locusts, which are a major source of concern. In these experiments, researcher's analysed vegetation patterns prior an outbreak, allowing them to identify the areas that had been most badly harmed. Evidence for a causal relationship between locust swarms and damaged vegetation has relied primarily on previous knowledge without involving factors. These studies of vegetation loss could be classified as local case studies with a limited geographic scope as opposed to more comprehensive studies. Ma et al. [66] investigated the relationship between biomass and leaf area index (LAI) measurements from Landsat during the presence of locusts.

Weiss [67] also evaluated MODIS 1 km for composite products that helps in mapping the damage produced by Australian plague locust nymph bands in order to better understand the extent of the devastation. Statistical analyses conducted prior to, during, and after the banding experiment revealed no statistically significant relationship between the extent and intensity of damage to vegetation. Weiss asserted that the spectral resolution and coarse spatial nature and temporal compositing procedures employed in their creation, meant that nymph bands feeding on plants could not be detected.

Additionally, Hunter et al. [68] investigated Australian plague locust bands that were detected from an aeroplane in addition to satellite-based analyses. It is possible to observe clearly in RGB photographs the locust nymphs accumulation and the injured vegetation. Using VHR satellite data, as well as unmanned aerial vehicles (UAVs) and high spatial-resolution sensors, a large aggregation of locusts and damaged plants should be geographically resolved.

VII. LOCUST MANAGEMENT

During the last few years, remote sensing has made a substantial contribution to the management of locust populations. A transition has occurred from single-picture land cover analysis to time-series based categorization in order to obtain findings for a variety of time intervals and, thus, to allow for long-term habitat and species distribution measurements.

Second, a district was established to manage the monitoring of habitats. According to Cracknell [69] in 1991, direct identification of habitat changes is either impossible or only plausible with a large amount of time elapsed.

Crooks and Archer [70] report that soil moisture data was either missing or restricted to operating bases in 2002. We can see from what we learnt in 2008 that there was still a great deal of confusion about the relationship between acridine danger and environmental monitoring at the time of the study. An era of remote sensing-based locust control is about to begin, thanks to recent advances in satellite images and the availability of new datasets, methodological tools, and computing power, which are working together to overcome these restrictions. The advent of MODIS data, which has increased spatial resolution (250–1000 m) and spectral resolution (36 channels), as well as a high temporal frequency, has aided and improved locust's management (daily). Since then, remote sensing-based research has centred on these challenges, in addition to analysing the temporal scale and statistical association between locusts and prior conditions.

To track vegetation changes over time, desert locust management relies primarily on the use of greenness maps, which have been shown to be effective. According to Piou et al. [58], using secondary measures based on time series data, it is possible to make an accurate estimate of the desert locust presence in a given area. This makes it possible to plan field surveys more effectively. Researchers have been able to explore the association between numerous ecological variables and the presence of locusts (e.g., EVI, GPP, FPAR, and LAI) by utilising well-established Analysis-Ready Data Sets based on MODIS data as a basis (ARD). During that time, components related to monitoring, prediction and early warning, have gained in importance as a result of advancements in rainfall calculation and weather forecasting, as well as breakthroughs in weather forecasting.

Gómez et al. [52] reported an encouraging strategy that asserted the value of soil moisture data, which was widely praised. As a result, Escorihuela et al. recommended the use of 1 km moisture in warning systems [51], which was accepted by national locust centres and the DLIS-FAO in particular. It has been modelled by Piou et al. [54] that employing soil moisture as a typical technique for preventive locust management could be beneficial. Desert locust incubation durations are brief, necessitating the availability of near real-time (NRT) records for appropriate analysis and follow-up operations in order to be effective. This is a demanding task, made even more difficult by the sheer expanse of the area that needs to be seen and recorded. Table 2 shows the dynamic indicators for studying locust outbreak.

Indicators		Spatial Resolution	Temporal Resolution
Dynamic indicators	PREC	0.05° (~5 km)	daily
	SM	0.1° (~10 km)	hourly
		0.03° (~3 km)	daily
	NDVI	1 km	daily

	LST	1 km	daily
Static indicators	SND	250 m	3-year
	CLY		
	SLT		
	CRF		
	LULC	100 m	5-year
	DEM	30 m	-

VIII. FUTURE WORK

It is necessary to have a complete pipeline in order for these stand-alone solutions to function properly. The development of an app that will allow entomologists to report locust sightings and assess concentrations of these invasive insects will be beneficial to the scientific community. In their current state, the models are far too large to be run on a mobile device, but work is being done to reduce their size so that they can only be run on mobile devices. The lack of an internet connection would allow this technique to be used in rural areas, where locusts are most numerous, without the requirement for a network connection. More research could be conducted to ensure that this strategy is effective with a greater diversity of locust species.

Because of the comparable instar growth of other grasshopper and locust species, it should theoretically be compatible with them as well. Once the information has been fully tested, it is possible to develop a categorization system for locusts and grasshoppers based on it. Even while it is capable of producing exceptional results, the outcomes are frequently jumbled and degrade the image quality, making it impossible to categorise the photographs taken. Because machine learning algorithms are incredibly difficult to train, their outputs may be unpredictable.

It is feasible to use the skills learned from this job on a variety of animals after being trained. Because there are apparent differences between different ages in the majority of animals, age categorization can theoretically be applied to every animal. Another possible application for this geo-tracking device, as well as others of similar design, is the tracking and monitoring of migrant populations. Due to the fact that animals such as locusts do not have distinct age phases, the challenge may need to be changed from an age estimation task to a regression task in which the numerical value of an animal age is identified, or even pooled together for category classification purposes.

CONCLUSION

Despite the fact that geomorphological measurements and radar-based soil moisture data have been used to track locust outbreaks in the past, their application to locust outbreaks remains unusual. However, despite substantial breakthroughs in remote sensing technology as well as broad adoption of this technology, the application of machine learning to assist in locust epidemic research and management is still in its early stages. Over the past 40 years, the use of ML for locust management and study has shown significant results. Efforts to monitor and anticipate outbreaks of the desert and plague locust have demonstrated the effectiveness and benefits of employing data for saving money and time when outbreaks occur.

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