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A review on internet of things-based stingless bee's honey production with image detection framework

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ABSTRACT

Honey is produced exclusively by honeybees and stingless bees which both are well adapted to tropical and subtropical regions such as Malaysia. Stingless bees are known for producing small amounts of honey and are known for having a unique flavor profile. Problem identified that many stingless bees collapsed due to weather, temperature and environment. It is critical to understand the relationship between the production of stingless bee honey and environmental conditions to improve honey production. Thus, this paper presents a review on stingless bee's honey production and prediction modeling. About 54 previous research has been analyzed and compared in identifying the research gaps. A framework on modeling the prediction of stingless bee honey is derived. The result presents the comparison and analysis on the internet of things (IoT) monitoring systems, honey production estimation, convolution neural networks (CNNs), and automatic identification methods on bee species. It is identified based on image detection method the top best three efficiency presents CNN is at 98.67%, densely connected convolutional networks with YOLO v3 is 97.7%, and DenseNet201 convolutional networks 99.81%. This study is significant to assist the researcher in developing a model for predicting stingless honey produced by bee's output, which is important for a stable economy and food security.

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1. INTRODUCTION

Modern agriculture is recognized as one of the world's most important economic pillars, providing for an essential human need despite several challenges, such as the rising demand for agricultural products [1]. One agricultural subsector where new technology might boost productivity, reduce production costs, and simplify the operations of rearing and breeding bee colonies is beekeeping [2]. To achieve its objective of developing into a high-income nation, Malaysia requires new high-income initiatives. One such potential project is the ruthless beekeeping industry's contribution to agriculture and society. Food, medicine, diet cosmetics, and other related applications are the main industries that employ the stingless bee product. Although Malaysia has discovered over 38 species of stingless bees, only four are widely used for farming: Heterotrigona, Geniotrigona thoracica, Heterotrigona itama, Lepidotrigona terminata, and Tetragonula leviceps [3]. On the other hand, are two species that are particularly active in the production of honey and propolis [4]. Stingless bees are pollinators who collect nectar and pollen from a wide variety of plants. Productive yields of stingless bee honey are predicted to alter the honey industry's supply and demand [5].

Despite this, beekeepers always confront a few difficulties when producing stingless bees in their colonies. Certain bee species, such as stingless bees, are highly vulnerable to climatic changes, particularly intense heat waves [6]. Beehive security, health, and weather conditions are a few instances of factors that could have an impact on the extraction of honey [7]. Bee mortality, particularly that of pupae, has been scientifically related to temperatures that reach as high as 38 °C [8]. A third of the globe's food supply relies on honeybees (Apis mellifera) for pollination. The production of honey by stingless bees is considerably less than that of Apis mellifera. This is why stingless bee honey fails to meet quality control criteria [9]. Temperature, humidity, smoke, and acoustic sounds produced by bee colonies are all important factors that influence bee productivity. The amount of honey harvested from the hives can be influenced by several crucial factors. The most common effects of extracting less honey are colony loss and an underproductive hive. This has an impact on the beekeeper's capacity to maintain hive health and honey production [10]. Both concerns are exacerbated by the low quality of the stingless bee habitat surrounding the farm. If the bees are positioned near their food source, a healthy stingless bee colony can be obtained. A lack of food may lead the bee colony to starve [11]. Certain steps must be taken to prevent the conditions that led to this predicament. As a result, it is critical to establish a model for predicting the stingless bee's actions so that any stingless bee's activities may be monitored and sustained.

In recent years, experts from across the world are increasingly interested in the value of modelling in predicting honey productivity. Several investigators have experimented with the automatic identification and counting of bees flying into and out of the beehive in conjunction with their investigations of sensory data. The researchers examined video that was captured with a camera which requires a bee-detecting device to analyze video streams [12]. Modern beekeepers' technologies facilitate the creation and use of internet of things (IoT) monitoring systems built into hives. This makes it feasible to acquire various information and to monitor remotely in real time. The next agricultural revolution, especially in precision agriculture, will be largely dependent on machine learning (ML) and the IoT [13]–[15]. Human labor can be minimized by using machine learning models using sensor data and clever approaches [16]. Insect classification and identification are two common duties that make use of machine learning techniques, which have recently been discovered in computer-aided photo classification systems. These challenges have been addressed by deep learning (DL) models, including convolutional neural networks (CNN), using the picture dataset. In a range of computer vision (CV) [17] and machine learning [18] problems, CNN has shown exceptional performance. Promising uses of DL and CV have been shown in the autonomous identification of bees and their health, including the detection of Varroa destructor and the sense of environmental variables like temperature and humidity [19]. DL is also a sophisticated data analysis and image processing technology that produces decent results and has a lot of potential. With these improvements, it is possible to classify a bee's health status using photos of the specimen, CV, and DL. However, to obtain photographs of bees, a previous task that can recognize images of bees in a scene and automatically crop the discovered bees into a new image must also exist.

A major issue in analyzing social insect behaviors such as bees and flies is the collection of quantitative data on many social insect behaviors like bees and flies over a long period of time. formerly, certain investigators relied on beekeepers' manual data collection from beehives [20]. This approach has worked quite well, but it has become less effective as the hives on a farm has increased. There have been reports of difficulties in gathering quantitative data on the daily activities of such small and fast-moving insects [21]. Since stingless bees are non-venomous and smaller in size than ordinary bees, an occurrence known as colony collapse disorder (CCD) has resulted in a substantial decline of stingless bee colonies species in 2006. Forager bees are unable to return to the nest due to CCD, leaving the queen and nursing bees with honey and bee bread [22]. Nonetheless, beekeepers may face some challenges that could lead to colony failure and underproduction. These issues can be attributed to several factors, including ambient temperature, humidity, and predators. The application of machine learning techniques in smart monitoring systems is still in its early stages, but it is rapidly gaining favor. As a result, the contributions of deep learning techniques to addressing the difficulties of smart monitoring systems in data processing and decision-making have been highlighted in this study. In comparison to Apis mellifera honey, the previous researcher discovered a comparatively low yield of stingless bee honey. According to [23], the amount of pure honey produced has gradually declined in recent years, owing mostly to inappropriate honey brood treatment.

Figure 1 illustrates that this research is significant because it aims to construct a stingless bee IoT monitoring system at *Pusat Penyelidikan Kelulut*, UiTM Terengganu Branch. Thus, it served as a site project and offered information about stingless bee behavior. Sensor data will aid academics and beekeepers in their work while also catalyzing bee conservation initiatives. Furthermore, through premium honey, this research will turn the stingless bee honey sector into a sustainable source of income for the Kelulut Research Centre and Malaysian beekeepers. Finally, the purpose of this study is to create a model for predicting stingless bee honey output, which is important for a stable economy and food security.

Figure 1. Stingless bee research centre, Universiti Teknologi MARA Terengganu Branch

Proper management of stingless bee colonies is crucial for their health and productivity. Beekeepers must ensure that the hives provide suitable conditions for the bees' growth and development. Traditionally, this involved manual inspections and observations, which were time-consuming and often disruptive to the bees. The development of innovative monitoring systems, such as IoT technology, has significantly improved colony management. These systems allow real-time tracking of hive conditions, including temperature, humidity, and food availability. Beekeepers can now make informed decisions based on accurate data without disturbing the bees, leading to more effective and efficient hive management. The impact of environmental factors on stingless bee behavior and honey production is a critical area of concern. Thus, this research is taken to analyze data taken form real honeybee hive and develop the predictive model on the honeybee production using CNN based on image processing. Lastly this research aims to validate the effectiveness of the developed model of stingless bee honey production. Result from this paper can guidance on the proactive approach allows beekeepers to take timely action and implement appropriate treatments to safeguard their colonies.

2. METHOD

The most effective approach to discover the review structure is to use an established publishing database's online search tool. The review structure for the honey production process of IoT-based stingless bees with image detection is shown in Figure 2. Many of the publications and proceedings that were picked for the literature review were found by those reviewers searching through the IEEE Xplore database, which is indexed in Science Direct and Scopus. Due to its availability of all kinds of publications encompassing peer reviews of products from databases, Google Scholar has also been utilized. The selection of search keywords, including CNN, stingless bee, IoT system, honey production, and image detection, was guided by the research framework. Every review paper was selected over a five-year period, starting in 2018 and concluding in 2022. Most of the journals and proceedings were chosen from 2018 to 2020. Only a few journals and proceedings were chosen between the years 2016 and 2017. The total number of review papers is about 54 papers.

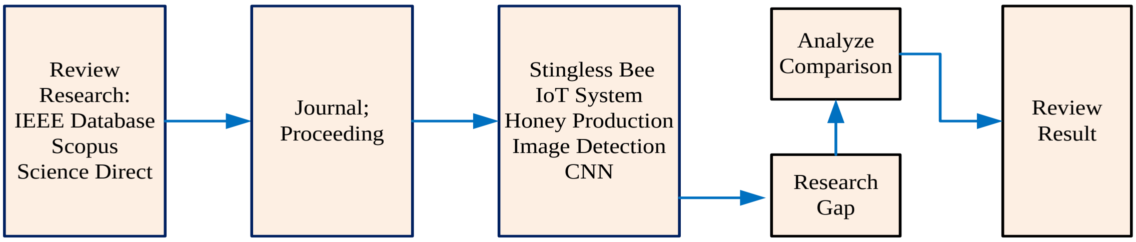

Figure 2. The review of IoT-based stingless bees' honey production with image detection framework

2.1. Design of IoT stingless bee

Extended transmission range is one of the benefits of low power wide area networks (LPWAN). Comparing IoT communication technology to current wireless communication technologies, the former offers greater coverage capacity, lower costs, and lower power usage [24]. The purpose of this study is to address the long-distance communication needs of intelligent agriculture systems by establishing an information transmission system using a long-range (LoRa) wireless network and connecting it to an upper computer system and sensor control system. Figure 3 shows how the IoT monitoring system for the stingless bee is designed. The components of this setup are gateways with a star topology configured and LoRa wide area network (WAN) end nodes. End nodes deliver payloads, such as sensory data, to the gateway to communicate. The gateway is constantly scanned for incoming data packets and that requires an internet connection to forward them to the things network (TTN) server. Using a node-red application, the data stream will be collected from the TTN server and pushed to Hostinger, a web hosting service. The data stream was saved in a MySQL database, which was subsequently connected to a web-based application and servers.

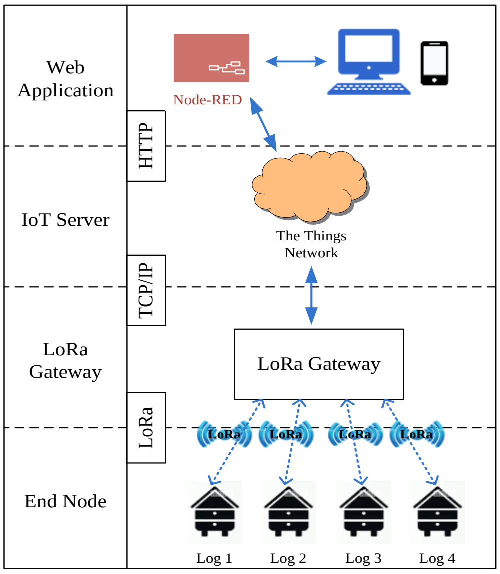

Figure 3. The architecture of the IoT monitoring system

The current research utilizes a LoRa wireless network to establish an information transmission system and incorporates it into a sensor control system and an upper computer system. Each end node's data was transmitted using radio frequency modulation (RFM) via a LoRa shield equipped with an RFM95W LoRa module. Low-data-rate transmission with strong interference rejection is provided, together with low-power and long-range spread-spectrum communication capabilities. Data from every sensor connected to the stingless beehive was handled by the Arduino microcontroller, which operated as the end node's central processing unit in the interim. A load cell that could measure up to 10 kg was used to track the beehive's weight over time. The weight data was used to calculate how much honey the beehive produced over time. Additionally, a smoke sensor that complies with MQ135 was put on each end node to monitor the ambient air quality. Each beehive's internal temperature and humidity were monitored in the interim using the DHT22 sensor. These components' connections to the beehives are depicted in Figure 4. The cayenne low power payload (LPP) format was used to combine the data from the temperature, weight, smoke, and humidity sensors into a single packet stream. These packet streams were routed to the LoRa Gateway once every 60 seconds.

An event-driven application that connects hardware, application programming interface (APIs), and online services can be made with Node-RED, a freely available open-source programming tool that has a flow-based editor. In addition to pre-built libraries and functions, it provides components for complex applications. In this study, data is retrieved from the TTN server and transmitted to the local and hosted databases using the node-red flow. Through the local network, a node-red user interface (UI) application had been linked to the local database. Concurrently, an additional database was hosted on the hostinger.com platform and connected to an online monitoring dashboard application that was viewable from any device with an internet browser.

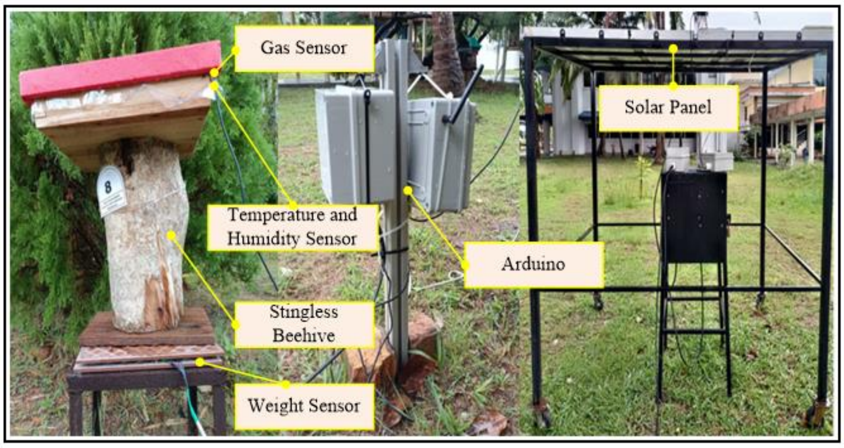

Figure 4. The solar panel, Arduino board, and sensor placement at the stingless beehives

2.2. Stingless bee honey predictions framework

A detailed methodology for precisely forecasting stingless bees' honey production is shown in Figure 5. This framework is logically divided into four stages, each of which is essential to the process. Phase 1 comprises the preliminary stages of data collection and processing, wherein unprocessed data related to different variables impacting honey production are obtained and prepared to guarantee uniformity and stability. During the second phase, known as data selection, the preprocessed data are subjected to in-depth analysis. This entails using data analysis methods to find relevant traits and trends in a dataset. Finding the factors that most significantly affect stingless bees' ability to produce honey is the goal. The careful selection of pertinent data points at this phase enhances the accuracy and effectiveness of later modelling stages. Phase 3, referred to as data development, involves further refining and transforming the selected dataset. Building an organized dataset is required for both training and verifying predictive models. Normalization, feature engineering, and data augmentation are a few of the preprocessing techniques that are used to guarantee the best possible model performance. The prediction model is trained using the improved dataset. Phase 4, which includes the model validation process, is the framework's climax. In this case, a CNN prediction model is used. CNNs are the best choice for this forecasting attempt because of their ability to recognize intricate spatial relationships within data. CNN takes advantage of the meticulously selected and cleaned dataset from phase.

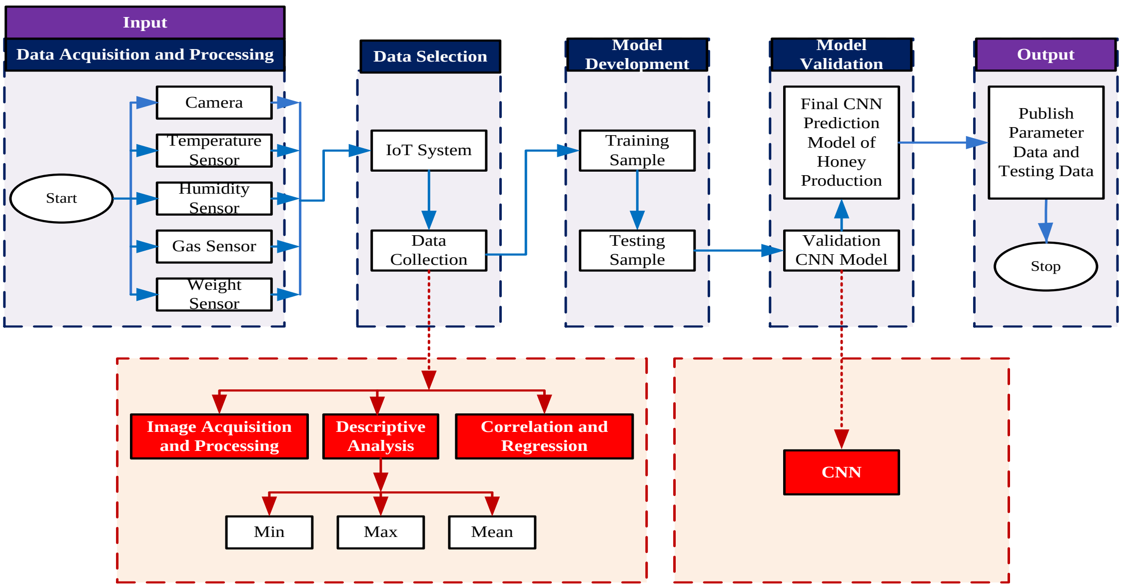

Figure 5. Framework of modelling the prediction of stingless bee’s honey

3. RESEACH GAPS

Initially, local beekeeping concentrated on several Apis species, such as apis cerana is a type of a local bee, apis mellifera is a commercial and imported bees and apis dorsata is the wild native giant bee 23. After the Malaysian Agricultural Research and Development Institute (MARDI) and the YAS began stingless beekeeping in the Malaysia Agro Exposition Park Serdang (MAEPS), Selangor, in 2011, the total number of beekeepers surged substantially, reaching around 1,000 persons. The physical traits of their wings distinguish stingless bees from other bees such as weak or absent sub-marginal cross veins and a second recurrent vein in the forewing. All stingless bees live in colonies of tens to hundreds of thousands of workers and, in most cases, a single queen. The number of men in the colony at any given time can range from zero to a dozen; males and workers are usually comparable in size and appearance, whereas queens are morphologically unique [25]. In general, stingless bee honey has a lower yield than honeybee honey. The market price of stingless bee honey, on the other hand, is higher than that of honey bee honey [26]. However, stingless bees, like many insect groups around the world, are endangered. The stingless bee business in Malaysia is facing serious issues, especially regarding queens and quality inconsistencies [27], which are threatened by habitat degradation, global climate change, and resource rivalry. Thus, beekeepers and researchers need to create a new and proper system to monitor and manage the environmental parameters of beehives as well as boost honey output.

3.1. IoT monitoring system

IoT is broadly used in many fields of smart agriculture [28]. There are many existing implementations of computerized identification on irrigation systems [29], pest detection [30], butterflies [31], crop production [32], varroa mites [33], and so on. However, the identification of the stingless bee relies very much on manual inspection by visually inspecting the hives and investigating their surroundings for possible problems. Because of the bees' habits, beekeeping is usually done away from homesteads [34]. As a result, farmers could lose a lot of money if they do not keep an eye on it regularly. So, the significance of this research provides automatic inspection as an option to migrate from conventional monitoring into an IoT monitoring system which provides more efficient monitoring of honey production as well as can increase yield production. The development of a stingless beehive monitoring system named iBees for Nature and Trigona Garden, which is in Kemaman, Terengganu has been presented. The system was developed to monitor the beehive with global positioning system (GPS) tracking, temperature and humidity sensor, and a microcontroller that combines with Wi-Fi. All the data such as longitude, latitude, temperature, and humidity are sent to an online cloud database. One previous research has shown a beekeeper can monitor their beehive in real-time as well as the system can trigger a notification to a user when any abnormal incidents happen to their hive and keep track of stingless beehive stolen. Meanwhile, the author of designed internet of things sensor systems embedded in beehives to collect heterogeneous data and provide real-time remote monitoring [35].

This study was carried out to forecast the processes that take place in beehives based on the outcomes of intricate prediction models that are used following the manipulation and normalization of the data. Two-class boosted decision trees, two-class averaged perceptron, two-class bayes point machines, and two-class support vector machines (SVM) are the algorithms that were covered in this paper. The two-class boosted tree approach, which has a 99% success rate in data classification and a 30% training set, demonstrated the best metrics among these algorithms after testing the data. New patterns between the hive's operations and environmental factors like temperature, humidity, air pressure, CO_2, and others can be found using datasets from beehives. Beekeepers have observed considerable declines in their hives in recent years because of a phenomenon known as CCD. Over the past few decades, there have been various attempts to identify the disaster's origins and potential solutions. A real-time automated beekeeping system was introduced by one system, which offers various insights regarding the beehives' weight, temperature, humidity, and pressure because of disruptions [36]. A DHT11 temperature and humidity sensor, an Arduino Uno based on the ATmega328P, a HX711 load cell sensor, and an FSR402 force sensor coupled to an ESP8266 Wi-Fi module for internet access are the components of a wireless mobile application that may be used to monitor these data. The interface created using the Blynk platform shows all available data and an alert sound for emergencies that require attention like sudden pressure surges exerted on the beehive log and temperatures beyond 40 °C.

To better understand bee behavior and assess the hives' overall health, numerous researchers have recently attempted to analyze audio and video recordings recorded at the beehives. a mechanism for a device that kept an eye on a beehive and informed the caretaker on the condition and efficiency of the colony. Temperature, humidity, and noise levels are measured by the system from within the hive. To track activity at the beehive entrance and monitor bee activity, a camera is put on the outside of the hive [37]. Algorithms analyze all this data to notify the beekeeper about the hive's health. The majority of agriculture algorithms employ machine learning to assess the hive's health included most agriculture prediction on fruits and vegetables [38]. A new system's conception and execution for gathering and tracking data was presented. The technology, called Beemon, is designed to automatically record sensor data, including weight, humidity, and temperature. Next, a ThingsBoard dashboard receives the sensor data using the message queuing telemetry transport (MQTT) protocol. Additionally, the Beemon system transfers audio and video recordings that are collected at the hives' entrance to an external server for examination and additional study. Beemon enables near real-time data collecting and runs constantly in an outdoor beehive environment.

3.2. Review in honey production

Predictions for stingless bee honey production are used as material to consider and help determine stingless bee honeybee output. Prediction of honey output is necessary not just for beginners but also for professional beekeepers or researchers, particularly during months when bees must be relocated owing to declining food supplies. The use of IoT technology and machine learning in honey production has allowed beekeepers and other researchers to integrate wireless sensors within beehives, allowing them to regulate the optimal conditions that promote honey production [37]. Table 1 shows the summary of advantages and limitations on honey production.

Table 1. Gaps of advantages and limitation on honey production

Area and research filed	Method/Algorithm	Advantage	Limitation
Honey yield prediction using Tsukamoto fuzzy inference system [39].	Tsukamoto's fuzzy inference system (FIS) method	Enable accurate prediction.	The FIS limited to the specific condition and variables.
Short-term prediction of honey production in Bosnia and Herzegovina using IoT [40].	Random tree regression algorithm	Honey weight production within the season to adjust the position of hives.	Data type of the most challenging seasons for beekeepers in the Country.
Summer weather conditions influence winter survival of honeybees (Apis mellifera) in the northeastern United States [41]	Random forest	Analysis of climatic variables, and adverse effects of both too-cool and too-hot summers were.	The data set.
Machine learning regression model for predicting honey harvests [10]	Gradient boosted regression	Predict the honey yield per hive with a mean average error (MAE) of 10.85 kg and classify the harvest into the correct quality category with 92% accuracy.	The accuracy of the prediction models maybe restricted by the availability of weather data.
Analysis of honey production with environmental variables [42]	SVM, Multi–layer perceptron regressor, Random forest regressor, K-neighbors regressor, Voting regressor, Ada boost regressor, Gradient boosting regressor.	The ensemble learning process models and increased the prediction success with the regression processes.	Algorithm proposed for this study could not show very high performance because they are stand alone.

3.3. Convolution neural network

Numerous computer vision and machine learning tasks have seen CNN perform exceptionally well. CNN is also used to address a few issues related to agriculture and food production, including remote sensing [43], plant classification [44], insect detection [45], yield prediction [46], and so forth. The researcher created a new system that uses video on the colony's entry ramp to identify, locate, and track the body parts of honeybees [47]. The new technique evaluates CNN's suitability for honeybee pose identification and builds on recent developments in the field of human pose estimation. Detecting entire bees on the entry ramp with over 95% accuracy without any prior tracking is possible with the suggested technique. This creates new opportunities for automated tracking of a wide variety of honeybee behavior outside of the lab and into the field when paired with trait identification, such as pollen-bearing. A way for creating a beehive health monitoring system is examined using image processing techniques. Two models make up the method: one recognizes bees in photos, and the other categories the health of the bees it finds. The defined methodology's primary contribution is higher model efficiency while keeping the state-of-the-art efficiency constant. Two databases were used to develop models for convolutional neural networks. The greatest results include 82% accuracy in identifying bee existence in an image and 95% accuracy in assessing a bee's health. The possibility of using image recognition methods on honeybee wings to distinguish between different subspecies of the species was explored using four models based on convolutional neural networks. A total of 9887 wing pictures from 7 subspecies and 1 hybrid were analyzed using ResNet50, MobileNet V2, Inception Net V3, and Inception ResNet V2 [48]. All models performed better than traditional morphometric evaluation, with individual wing categorization accuracy rates exceeding 0.92. The Inception models had the highest accuracy, recall, and precision scores for many of the classes. In the meanwhile, training has been conducted using the inception-ResNet-v2 model [46]. The purpose of this work is to identify agricultural diseases automatically. The data collection, which consists of 27 disease photos from 10 crops, comes from the 2018 AI Challenger Competition public data set. A multi-layer convolution and a cross-layer direct edge are features of the residual network unit. Once the combined convolution operation is finished, the link into the rectified linear unit (ReLU) function activates it. The efficiency of this model is demonstrated by the experimental findings, which reveal that its total recognition accuracy is 86.1%.

Ten different types of pests that are present in the paddy crop are recognized using deep convolutional neural networks (DCNN). Around 3,549 pest photos that harm rice crops are included in the data repository; as deep learning works with larger datasets; data augmentation is done. The ResNet-50 model's layers and hyperparameters are adjusted using the transfer learning technique on the pest dataset. The model's effective performance in classifying pest diseases is described by the derived resultant value. The refined ResNet-50 model outperformed the other models with an accuracy of 95.012% when the outcome of the analysis was compared. CNN ensembles based on several topologies, including ResNet50, EfficientNetB0, GoogleNet, ShuffleNet, MobileNetv2, and DenseNet201, were created [49]. Various Adam variations are optimized for pest identification in these topologies. Based on DGrad, two new Adam algorithms for deep network optimization are put forth that scale the learning rate. Six CNN architectures, with different optimization functions, were trained using three pest data sets: Xie2 (D0), big IP102, and Deng (SMALL). Several performance metrics were used to compare and assess the ensembles. The CNNs were integrated utilizing the various Adam variations by the ensemble that performed the best. All three bug data sets saw the desired outcome: 95.52% on Deng, 74.11% on IP102, and 99.81% on Xie2. The researcher created a new system that uses video on the colony's entry ramp to identify, locate, and track the body parts of honeybees [50]. The updated system expands upon recent advances in CNN for human pose estimation and assesses its suitability for honeybee pose detection. The proposed system achieves over 95% accuracy in the pure detection of complete bees on the entrance ramp without any prior tracking. When combined with trait detection, such as pollen-bearing, this opens new avenues for automated tracking of a diverse range of honeybee behavior outside of the laboratory and into the field.

3.4. Automatic image detection

There are still few studies on stingless beehives, according to earlier study, although some work has been done on developing beehive monitoring systems and utilizing CNN to estimate honey production. Thus, this research proposed the implementation of the prediction of stingless bee honey yield based on bee movement using CNN. Table 2 shows the articles which discuss the parameters and method used to determine the potential model of prediction.

Table 2. Automatic detection method

Authors	Samples	Sensor	Method/Technique	Efficiency
Xia *et al.*, 2018 [51]	24 species of crop insects	Image database	CNN, Region proposal network, VGG19	89.22%
Rodríguez *et al.*, 2018 [47]	Honeybee	Digital camera	CNN, Hungarian algorithm	95%
Patel and Vaghela, 2019 [52]	Crop Pest	Image database	CNN	98.67%
Wang *et al.*, 2020 [53]	Pest	Image database	Deep CNN, VggA, VGG16, Inception V3, ResNet5, CPAFNet	>92%
Zhong *et al.*, 2018 [54]	Flying insect	Raspberry Pi	YOLO, SVM	92.5%
Ai *et al.*, 2020 [48]	Insect Pest	Dataset from the crop disease recognition competition of the 2018 Artificial Intelligence Challenger Competition	Inception-ResNet-v2	86.1%
Nanni *et al.*, 2022 [49]	Pest	Deng (SMALL), large IP102, and Xie2 (D0) pest data sets	(EfficientNetB0, ResNet50, GoogleNet, ShuffleNet, MobileNetv2, and DenseNet201)	95.52% on Deng, 74.11% on IP102, and 99.81% on Xie2
Jomtarak *et al.*, 2021 [55]	Mosquito	Image database	DCNN, YOLO v3	97.7%
Liu *et al.*, 2022 [56]	Crop Pest	Image database	VGG16 and Inception-ResNet-v2	97.71%
Kelley *et al.*, 2021 [57]	Bee	Image dataset Bee spotter	Faster R-CNN, Resnet 101+FPN	91%
Tetila *et al.*, 2020 [58]	Soybean pest	Image dataset	Inception-v3, Resnet-50, VGG-16, VGG-19 and Xception, SVM	93.82%

4. CONCLUSION

As a conclusion a detailed review on IoT-based stingless bee's honey production with image detection framework has been explored. Results present comparative research gaps in an innovative approach that uses IoT technology and algorithms to identify and categorize the different bee species. Gaps on honey production and machine learning techniques related to CNN, YOLO, regression method has been derived. Lastly, automatic image detection has also been reviewed and presents the best techniques to identify and predict the honeybee's production. This result will be used as guidance in the development and deployment of prediction model for honeybee productivity by using pattern of image processing.

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REFERENCES

[1] H. Arruda, V. Imperatriz-Fonseca, P. de Souza, and G. Pessin, "Identifying bee species by means of the foraging pattern using machine learning," in *2018 International Joint Conference on Neural Networks (IJCNN)*, Jul. 2018, pp. 1–6, doi: 10.1109/IJCNN.2018.8489608.

[2] K. Dineva and T. Atanasova, "Applying machine learning against beehives dataset," in *International Multidisciplinary Scientific GeoConference Surveying Geology and Mining Ecology Management*, Jun. 2018, pp. 35–42, doi: 10.5593/sgem2018/6.2/S25.005.

[3] M. M. Ismail and W. I. W. Ismail, "Development of stingless beekeeping projects in Malaysia," *E3S Web of Conferences*, vol. 52, Aug. 2018, doi: 10.1051/e3sconf/20185200028.

[4] S. M. Mohammad, N.-K. Mahmud-Ab-Rashid, and N. Zawawi, "Stingless bee-collected pollen (Bee Bread): Chemical and microbiology properties and health benefits," *Molecules*, vol. 26, no. 4, Feb. 2021, doi: 10.3390/molecules26040957.

[5] M. F. Jaapar, R. Jajuli, M. R. Mispan, and I. A. Ghani, "Foraging behavior of stingless bee Heterotrigona itama (Cockerell, 1918) (Hymenoptera : Apidae : Meliponini)," AIP Conference Proceedings, vol. 1940, no. 1, 2018, doi: 10.1063/1.5027952.

[6] P. Bharman, S. Ahmad Saad, S. Khan, I. Jahan, M. Ray, and M. Biswas, "Deep learning in agriculture: A review," *Asian Journal of Research in Computer Science*, pp. 28–47, Feb. 2022, doi: 10.9734/ajrcos/2022/v13i230311.

[7] N. H. Khairul Anuar *et al.*, "IoT platform for precision stingless bee farming," in *2019 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS)*, Jun. 2019, pp. 225–229, doi: 10.1109/I2CACIS.2019.8825089.

[8] M. A. A. Che Ali, B. Ilias, N. A. Rahim, S. A. Abdul Shukor, A. H. Adom, and M. A. H. Saad, "A review on the stingless beehive conditions and parameters monitoring using IoT and machine learning," *Journal of Physics: Conference Series*, vol. 2107, no. 1, Nov. 2021, doi: 10.1088/1742-6596/2107/1/012040.

[9] M. Hrncir, S. Jarau, and F. G. Barth, "Stingless bees (Meliponini): Senses and behavior," *Journal of Comparative Physiology A*, vol. 202, no. 9–10, pp. 597–601, Oct. 2016, doi: 10.1007/s00359-016-1117-9.

[10] T. Campbell, K. W. Dixon, K. Dods, P. Fearns, and R. Handcock, "Machine learning regression model for predicting honey harvests," *Agriculture*, vol. 10, no. 4, Apr. 2020, doi: 10.3390/agriculture10040118.

[11] M. T. Miskon, M. A. A. Razak, H. Jaafar, N. Hassan, and R. Mahmood, "A lora-based testbed development for stingless bee monitoring system," *TEM Journal*, vol. 11, no. 2, pp. 712–718, 2022, doi: 10.18442121/TEM112-26.

[12] S. Ávila, M. R. Beux, R. H. Ribani, and R. C. Zambiazi, "Stingless bee honey: Quality parameters, bioactive compounds, health-promotion properties and modification detection strategies," *Trends in Food Science & Technology*, vol. 81, pp. 37–50, Nov. 2018, doi: 10.1016/j.tifs.2018.09.002.

[13] A. R. M. Soleh, N. Sulaiman, and M. Kassim, "Smart IoT-based aquarium monitoring system on anabas testudineus habitat using NodeMcu and blynk platform," in *2023 19th IEEE International Colloquium on Signal Processing & Its Applications (CSPA)*, Mar. 2023, pp. 292–297, doi: 10.1109/CSPA57446.2023.10087383.

[14] A. K. P. Mohd Daud, N. A. Sulaiman, Y. W. M. Yusof, and M. Kassim, "An IoT-based smart aquarium monitoring system," in *2020 IEEE 10th Symposium on Computer Applications & Industrial Electronics (ISCAIE)*, Apr. 2020, pp. 277–282, doi: 10.1109/ISCAIE47305.2020.9108823.

[15] M. K. R. Effendi, M. Kassim, N. A. Sulaiman, and S. Shahbudin, "IoT smart agriculture for aquaponics and maintaining goat stall system," *International Journal of Integrated Engineering*, vol. 12, no. 8, Aug. 2020, doi: 10.30880/ijie.2020.12.08.023.

[16] A. Sharma, A. Jain, P. Gupta, and V. Chowdary, "Machine learning applications for precision agriculture: A comprehensive review," *IEEE Access*, vol. 9, pp. 4843–4873, 2021, doi: 10.1109/ACCESS.2020.3048415.

[17] A. S. Kini, P. K. V. Reddy, and S. N. Pai, "Techniques of deep learning and image processing in plant leaf disease detection: A review," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 3, Jun. 2023, doi: 10.11591/ijece.v13i3.pp3029-3040.

[18] J. Wu, "Introduction to convolutional neural networks," Nanjing University, China, 2017.

[19] D. Braga, A. Madureira, F. Scotti, V. Piuri, and A. Abraham, "An intelligent monitoring system for assessing bee hive health," *IEEE Access*, vol. 9, pp. 89009–89019, 2021, doi: 10.1109/ACCESS.2021.3089538.

[20] R. Tashakkori, A. S. Hamza, and M. B. Crawford, "Beemon: An IoT-based beehive monitoring system," *Computers and Electronics in Agriculture*, vol. 190, Nov. 2021, doi: 10.1016/j.compag.2021.106427.

[21] P. Marchal, A. Buatois, S. Kraus, S. Klein, T. Gomez-Moracho, and M. Lihoreau, "Automated monitoring of bee behaviour using connected hives: Towards a computational apidology," *Apidologie*, vol. 51, no. 3, pp. 356–368, Jun. 2020, doi: 10.1007/s13592-019-00714-8.

[22] A. Nurhiman, A. Almira, R. Raffiudin, M. N. Indro, A. Maddu, and T. Sumaryada, "Automatic monitoring system of Apis cerana based on image processing," *IOP Conference Series: Earth and Environmental Science*, vol. 948, no. 1, Dec. 2021, doi: 10.1088/1755-1315/948/1/012090.

[23] P. Vit, S. R. Pedro, and D. Roubik, *Pot-honey: A legacy of stingless bees*. Springer Science & Business Media, 2013.

[24] L. Jing and Y. Wei, "Intelligent agriculture system based on LoRa and Qt technology," in *2019 Chinese Control And Decision Conference (CCDC)*, Jun. 2019, pp. 4755–4760, doi: 10.1109/CCDC.2019.8833476.

[25] S. P. Kek, N. L. Chin, Y. A. Yusof, S. W. Tan, and L. S. Chua, “Classification of entomological origin of honey based on its physicochemical and antioxidant properties,” *International Journal of Food Properties*, vol. 20, pp. S2723–S2738, Dec. 2017, doi: 10.1080/10942912.2017.1359185.
[26] C. Edmund and M. Ab. Rahman, “Smart stingless beehive monitoring system,” in *Computational Science and Technology: 7th ICCST 2020, Pattaya, Thailand, 29–30 August, 2020*, Singapore: Springer Singapore, 2021, pp. 537–549.
[27] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour, and E.-H. M. Aggoune, “Internet-of-things (IoT)-Based smart agriculture: toward making the fields talk,” *IEEE Access*, vol. 7, pp. 129551–129583, 2019, doi: 10.1109/ACCESS.2019.2932609.
[28] P. Chandana *et al.*, “An effective identification of crop diseases using faster region based convolutional neural network and expert systems,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 6, Dec. 2020, doi: 10.11591/ijece.v10i6.pp6531-6540.
[29] A. Deroussi *et al.*, “A novel autonomous remote system applied in agriculture using transmission control protocol,” *International Journal of Reconfigurable and Embedded Systems (IJRES)*, vol. 11, no. 1, pp. 1–12, Mar. 2022, doi: 10.11591/ijres.v11.i1.pp1-12.
[30] V. Malathi and M. P. Gopinath, “Classification of pest detection in paddy crop based on transfer learning approach,” *Acta Agriculturae Scandinavica, Section B-Soil & Plant Science*, vol. 71, no. 7, pp. 552–559, 2021, doi: 10.1080/09064710.2021.1874045.
[31] B. Ivosevic, Y.-G. Han, and O. Kwon, “Monitoring butterflies with an unmanned aerial vehicle: current possibilities and future potentials,” *Journal of Ecology and Environment*, vol. 41, no. 1, Dec. 2017, doi: 10.1186/s41610-017-0028-1.
[32] A. A. Araby *et al.*, “Smart IoT monitoring system for agriculture with predictive analysis,” in *2019 8th International Conference on Modern Circuits and Systems Technologies (MOCAST)*, May 2019, pp. 1–4, doi: 10.1109/MOCAST.2019.8741794.
[33] L. Chazette, M. Becker, and H. Szczerbicka, “Basic algorithms for bee hive monitoring and laser-based mite control,” in *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*, Dec. 2016, pp. 1–8, doi: 10.1109/SSCI.2016.7850001.
[34] H. Kyampeire, “A beehive intrusion and honey monitoring system,” Dissertation, Busitema University, 2016.
[35] H. A. Rosli, N. Abdul Malik, and Y. A. Ahmad, “IoT based monitoring system for stingless bees colony in IIUM,” *Journal of Physics: Conference Series*, vol. 2312, no. 1, Aug. 2022, doi: 10.1088/1742-6596/2312/1/012088.
[36] A. Shaout and N. Schmidt, “Bee hive monitor,” in *2019 International Arab Conference on Information Technology (ACIT)*, Dec. 2019, pp. 52–57, doi: 10.1109/ACIT47987.2019.8990982.
[37] K. Dineva and T. Atanasova, “Model of modular IoT-based bee-keeping system,” *European Simulation and Modelling Conference ESM*, pp. 404–406, 2017.
[38] S. Tkatek, S. Amassmir, A. Belmzoukia, and J. Abouchabaka, “Predictive fertilization models for potato crops using machine learning techniques in Moroccan Gharb region,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 5, pp. 5942–5950, Oct. 2023, doi: 10.11591/ijece.v13i5.pp5942-5950.
[39] T. Hastono, A. J. Santoso, and Pranowo, “Honey yield prediction using Tsukamoto fuzzy inference system,” in *2017 4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)*, Sep. 2017, pp. 1–6, doi: 10.1109/EECSI.2017.8239150.
[40] S. Sakanovic, N. Dogru, D. Keco, and J. Kevric, “Short-term prediction of honey production in Bosnia and Herzegovina using IoT,” in *2019 8th Mediterranean Conference on Embedded Computing (MECO)*, Jun. 2019, pp. 1–4, doi: 10.1109/MECO.2019.8760012.
[41] M. Calovi, C. M. Grozinger, D. A. Miller, and S. C. Goslee, “Summer weather conditions influence winter survival of honey bees (Apis mellifera) in the northeastern United States,” *Scientific Reports*, vol. 11, no. 1, 2021, doi: 10.1038/s41598-021-81051-8.
[42] E. Atagun and A. Aalbayrak, “Analysis of honey production with environmental variables,” in *2021 6th International Conference on Computer Science and Engineering (UBMK)*, Sep. 2021, pp. 462–465, doi: 10.1109/UBMK52708.2021.9558933.
[43] C. Yao, Y. Zhang, Y. Zhang, and H. Liu, “Application of convolutional neural network in classification of high resolution agricultural remote sensing images,” *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XLII-2/W7, pp. 989–992, Sep. 2017, doi: 10.5194/isprs-archives-XLII-2-W7-989-2017.
[44] S. Razavi and H. Yalcin, “Using convolutional neural networks for plant classification,” in *2017 25th Signal Processing and Communications Applications Conference (SIU)*, May 2017, pp. 1–4, doi: 10.1109/SIU.2017.7960654.
[45] H. Kuzuhara, H. Takimoto, Y. Sato, and A. Kanagawa, “Insect pest detection and identification method based on deep learning for realizing a pest control system,” in *2020 59th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE)*, Sep. 2020, pp. 709–714, doi: 10.23919/SICE48898.2020.9240458.
[46] S. Khaki, L. Wang, and S. V. Archontoulis, “A CNN-RNN framework for crop yield prediction,” *Frontiers in Plant Science*, vol. 10, Jan. 2020, doi: 10.3389/fpls.2019.01750.
[47] I. F. Rodríguez, K. Branson, E. Acuña, J. L. Agosto-Rivera, T. Giray, and R. Mégret, “Honeybee detection and pose estimation using convolutional neural networks,” *Congres Reconnaissance des Formes, Image, Apprentissage et Perception (RFIAP)*, 2018.
[48] Y. Ai, C. Sun, J. Tie, and X. Cai, “Research on recognition model of crop diseases and insect pests based on deep learning in harsh environments,” *IEEE Access*, vol. 8, pp. 171686–171693, 2020, doi: 10.1109/ACCESS.2020.3025325.
[49] L. Nanni, A. Manfè, G. Maguolo, A. Lumini, and S. Brahnam, “High performing ensemble of convolutional neural networks for insect pest image detection,” *Ecological Informatics*, vol. 67, Mar. 2022, doi: 10.1016/j.ecoinf.2021.101515.
[50] D. De Nart, C. Costa, G. Di Prisco, and E. Carpana, “Image recognition using convolutional neural networks for classification of honey bee subspecies,” *Apidologie*, vol. 53, no. 1, Mar. 2022, doi: 10.1007/s13592-022-00918-5.
[51] D. Xia, P. Chen, B. Wang, J. Zhang, and C. Xie, “Insect detection and classification based on an improved convolutional neural network,” *Sensors*, vol. 18, no. 12, Nov. 2018, doi: 10.3390/s18124169.
[52] P. P. Patel and D. B. Vaghela, “Crop diseases and pests detection using convolutional neural network,” in *2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, Feb. 2019, pp. 1–4, doi: 10.1109/ICECCT.2019.8869510.
[53] J. Wang, Y. Li, H. Feng, L. Ren, X. Du, and J. Wu, “Common pests image recognition based on deep convolutional neural network,” *Computers and Electronics in Agriculture*, vol. 179, Dec. 2020, doi: 10.1016/j.compag.2020.105834.
[54] Y. Zhong, J. Gao, Q. Lei, and Y. Zhou, “A vision-based counting and recognition system for flying insects in intelligent agriculture,” *Sensors*, vol. 18, no. 5, May 2018, doi: 10.3390/s18051489.
[55] R. Jomtarak *et al.*, “Performance of deep convolutional neural network approaches and human level in detecting mosquito species,” *bioRxiv*, 2021.
[56] Y. Liu, X. Zhang, Y. Gao, T. Qu, and Y. Shi, “Improved CNN method for crop pest identification based on transfer learning,” *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–8, Mar. 2022, doi: 10.1155/2022/9709648.
[57] W. Kelley, I. Valova, D. Bell, O. Ameh, and J. Bader, “Honey sources: Neural network approach to bee species classification,” *Procedia Computer Science*, vol. 192, pp. 650–657, 2021, doi: 10.1016/j.procs.2021.08.067.
[58] E. C. Tetila *et al.*, “Detection and classification of soybean pests using deep learning with UAV images,” *Computers and Electronics in Agriculture*, vol. 179, Dec. 2020, doi: 10.1016/j.compag.2020.105836.

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