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A REAL-TIME FRAMEWORK FOR MONITORING AND ANALYSING BEE BEHAVIOUR DURING POLLEN FORAGING

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Abstract

Increases in temperature and light intensity led to a rise in the quantity of forag- ing excursions for pollen, while increases in relative humidity, precipitation, and wind speed resulted in a decrease. When there was a lot of rain or a light breeze, there was a noticeable decrease in pollen foraging activity. This study shows the effectiveness of the suggested imaging technology in addition to quantitatively presenting the impact of environmental conditions on pollen foraging behavior. The imaging system can be mechanizedused as a dependable and effective tool to help beekeepers manage their hives and to help researchers better understand the foraging behavior of honey bees. The maintenance of a healthy ecosystem depends heavily on honeybees. In addition to producing honey, beeswax, and royal jelly, bees also aid in pollination. Although beekeeping has a long history and significant global economic potential, swarming is still a major obstacle to sustaining profitability. Since swarming reduces the number of bees in hives and affects honey output, it has a major effect on beekeepers' profitability. Swarming is a common colony reproductive process in honeybees. Therefore, it is crucial to monitor these beehives in order to keep an eye on their erratic behavior. Visual inspection of hives, temperature monitoring, or machine learning analysis of auditory data can all be used to anticipate swarms. Since acoustic monitoring circumvents the limitations of visual examinations and is unaffected by environmental variables like temperature, it is essential for identifying changes in colony behavior. A mixed machine learning approach to bee behavior analysis that prioritizes spatial detection and a temporal activity classification. Our method enables efficient real-time monitoring and classification of bee activity, yielding valuable data for ecological research and precision farming. The system exhibits significant improvements in behavioral classification and precision in detection when evaluated on a custom-labeled video dataset. We study techniques such as Multi-Layer Perceptron (MLP) and Logistic Regression to address the issue of identifying a queen bee in a hive. MFCC are utilized for feature extraction and as input for models of classification in order to distinguish between hives with and without a queen bee.

***Keywords**:* Phase transitions, selforganization, honeybees, insect foraging

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1. INTRODUCTION

Honey bees & bee species are necessary pollinators, providing critical services to crops and wild plants. As such, they underpin biodiversity and human food security. Monitoring bee activity – especially foraging flights and nesting – yields valuable indicators of colony health and stress from environmental factors. In recent years, "precision apiculture" has emerged, applying digital tools to protect bees and optimize hive productivity. Automated video systems at hive entrances can capture rich behaviours data (e.g. entry/exit events and pollen loads) with minimal invasion. For example, CNN-based monitoring has been shown to detect entrance/exit events and pollen carrying in real time, a key advance for scalable colony health assessment. Behavioural patterns observed at the landing board (foraging trips, fanning, guarding, etc.) vary with time of day and weather, so robust vision systems promise new insights into how environmental conditions affect bee activity.

Pollinators, especially honeybees, are critical for maintaining biodiversity and supporting global agriculture. Understanding their foraging behaviour, environmental sensitivity, and colony dynamics provides valuable insights into ecosystem health. Traditional observation methods are time-consuming, often biased, and lack real-time capability. Latestimprovements in computer vision & ML, predominantly deep learning, offer transformative potential for automating and scaling up behavioural analysis in natural settings.

We investigate if the aforementioned conditions occur in honeybees for the conditions of aging. The main difference between honeybee and ant scouting is that the former does not use pheromone trails. However, we propose that phase transitions and bistability are also discovered for honeybee using a straightforward but realistic model and computer simulation. We examine bistability as it happens when several sources of food are used, as well as the scenario where there is just one source of food. Each of the stages discovered correlate to less and more succeeding colony organize themselves; respectively, as well as low and high foraging. Understanding the fitness impacts that arise from adjustments to a certain parameter, such group size, is essential if we wish to comprehend why developed natural systems exhibit particular values for the parameter. This is especially important when there are abrupt changes in fitness because there are many benefits to a very small additional investment, making it an alluring path for evolution. These abrupt changes also occur in the degree of polytheism (division of labor) for certain social species of insects, which has a positive but nonlinear relationship with colony size. The numbers and activities of various agents are the most important environmental parameters for an agent in phase transition events, which are essentially a "numbers game." In addition to providing details about how social insects function, it's attainable that findings about these insects could also provide hints for systems of totally distinct agents (robots, molecules, people).

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First, we provide an overview of several fundamental facts regarding honeybee foraging. We then create a model of the foraging process that is heavily sufficient but still modest. We investigate some of this model's characteristics that are connected to foraging effectiveness through simulation, both for one source of food and for several. We conclude with a few hints of the results' applicability and potential directions for further study.

One of the primary functions of any self-preserving organism, or even super organism, is feeding. Feeding is an activity that both the colony and individual honeybees engage in. Worker bees collect pollen and nectar, transport it to the hive, and then store it in the hive. Honey is created from the nectar. While the foraging workers have the opportunity to feed on their own, the queen, other workers, larvae, and drones must rely on the colony to function. All bees depend on colony operations over the winter months in order to utilize the honey and pollen stores that have been accumulated. Under normal circumstances, a colony will typically have a wide variety of sources of food (flower regions) to select from. By scouting the environment, worker bees will find potential food sources. When bees recognize the source of food and have found a worker bee to store their load efficiently, they will waggle dance on a section of vertical combed in the hive called the floor for dancing. This is a sign that the hive can manage an increase in incoming food. Each of these dances provides the bees observing the known food supply with knowledge concerning its general direction, distance, and quality, most likely exclusively through hands-on means. While it often takes five tries before a target is really located, onlookers may then decide to hunt and nourishment at that food supply themselves. The number of dances accomplished for a certain food source and the duration of those dancing are directly correlated with the likelihood that an onlooker bee will be recruited for that source, which is correlated with the quality of the source. Better sources of food will therefore regularly attract more bees. The actual process of choosing a food source is more complicated than we have depicted here. However, it is helpful to simplify in order to see how circumstances in such an approach might operate. Starting with simple questions is also helpful; we had two sets of them.

The study of bee behavior is crucial for understanding ecological dynamics, pollination patterns, and the early detection of colony health issues. Traditional manual monitoring methods are labour-intensive and often lack precision. With the advancement of computer vision and deep learning, automated systems have arisen as dominant tools for analysing bee motionin real-time.

For reliable bee detection and behavioral evaluation, this work suggests an integrated YOLOv8-LSTM approach that combines the advantages of momentary and spatial deep learning approaches. The model blends an LSTM network, which is ideal for modeling temporal dependencies in sequential data, with YOLOv8, a cutting-edge object identification framework.

YOLOv8 is very good at quickly and accurately identifying bees in individual video frames, offering accurate classification and localization. It does not, however, provide the temporal context required to comprehend intricate behaviors like competitive encounters, feeding patterns, or waggle dance. This is addressed by integrating an LSTM layer, which allows the system to recognize behavioral patterns and changes over time by processing sequences of detected bee positions and motions.

The system's capacity to follow and evaluate bee behavior in addition to detecting them is improved by this hybrid technique, which has important applications in ecological monitoring, precision agriculture, and environmental conservation initiatives.

1.1.

1.1.1. Objectives

1. **Create and deploy** a YOLOv8-LSTM integrated model that combines sequential temporal modeling and real-time object identification for thorough bee monitoring.
2. **Analyse foraging dynamics and guard behaviours**to apply LSTM networks for analyzing temporal patterns in bee movement, enabling identification of behaviors such as foraging, resting, and waggle dancing.
3. **Assess the performance of LSTM networks** for analyzing temporal patterns in bee movement, enabling identification of behaviors such as foraging, resting, and waggle dancing.

2. LITERATURE REVIEW

Several colony statuses can be seen throughout the life cycle of the honey bee colony. In some circumstances, certain states (such as swarming or broodless condition) might have a detrimental effect on the growth of the colony, perhaps leading to its demise and raising beekeeping expenses. The honey bee colony's ability to reproduce, however, is shown when it is at the active brood rearing stage (at the preferred time). Without entering the hive, a beekeeper can improve his apiary management by understanding the state of the bee colony at any given time. This allows him to plan ahead for future operations. The "Application of Information Technologies in Precision Apiculture" (ITAPIC) initiative used one sensor for temperature per honey bee hive to monitor the colonies. This provides sufficient information to analyze temperature dynamics and identify trends in the specified honey bee colony conditions. A method for identifying the status of a honey bee colony can be created using this data. Either using neural networks or analyzing the temperature data and creating algorithms for every state of the honey bee colony can do this. Numerous activities, especially those involving data processing and classification, make extensive use of neural networks. The authors of this research provide a technique for detecting honey bee colony state (the start of the brood rearing period and swarming) utilizing neural networks with supervised training [1].Both the ecosystem and humans depend on honey bees; pollination depends on honey bees, while humans use bee products for a variety of uses. Scholars, beekeepers, and bee breeders must be able to identify the subcategories of honey bees. Because traditional identifying techniques are time-intensive and expensive, a precise and efficient solution is needed. Using a dataset of seven honey bee subspecies, this research suggests a computer vision-based approach for classifying honey bee variants. The Transfer Learning (TL) technique has been used because there aren't enough annotated images available to train a model.The primary Convolutional Neural Network designing has been the Inception v3 model, which was first trained on the ImageNet dataset and subsequently refined on the honey bee dataset. The impact of a tiny and unbalanced dataset has also been lessened by the use of image augmentation techniques. With a weighted average F1 score of 0.94 and an accuracy of 94%, the Transfer Learning-based v3 Inception model was calibrated using the Sigmoid a focal point loss function. This illustrates how computer vision can be used for honey bee classification [2]. A popular task that depends on individual experiences is the Artificial Neural Network (ANN). Among the most widely used and well-liked methods for feed forward neural network training optimization are the Back-Propagation algorithm and the nature-inspired meta-heuristic. The ABC algorithm (Artificial Bee Colony) is a meta-heuristic method inspired by nature that finds food sources for its colony by studying the movements of intelligent honey bees. The ABC methodology, which uses an opposition-chaos initiation method with well-rounded exploiting and investigating skills, is created to improve the artificial bee hive algorithm's performance. ABC enhances an ANN's design characteristics, including each neuron's role of transfer and synaptic weight, to increase accuracy while minimizing error. The analysis was performed over a conventional classifier dataset, throwing light on performance [3]. Robbery of honey bee hives is a typical occurrence during periods of low nectar availability. Bees from neighboring hives may raid colonies that are unable to defend each other and have accumulated supplies such as honey or fluid. Bee Keepers frequently try various techniques to avoid or stop a robbery, as well as steps to keep the plundered hive alive, but the majority of those attempts fail, and the targeted hive collapses. Analysis of audio and video recordings taken at a hive before and after a heist. The targeting hive was a top-bar hive that had been stolen by bees from surrounding colonies [4]. In this project, we constructed a honey bee monitoring system using computer vision and cutting-edge technology, with the goal of improving its comprehension of Colony Collapse Disorder, honey bee behavior, population loss, and average hive wellness. By installing the device at the point of entry and providing real-time data, beekeepers may use an account-based website to closely monitor the activity and health of the hive. Our machine learning-based monitoring system tracks honey bees accurately, tracks pollen-gathering activity, and detects Varroa mites without disturbing the bees. Additionally, we guarantee that cost-effective technology was used in the construction of this monitoring system, creating it available to apiary operations of varying sizes, that includes hobbyists, corporate beekeeping organizations, and scholars. Our data-trained YOLOv7-tiny architecture serves as the foundation for the inferring models utilized to identify mites, pollen, and honey bees. For honey bee model recognition, the precision and recall values are 0.981 and the F1-score is 0.95. The precision and recall values for our pollen and mite object detection model are 0.821 and 0.95, respectively. With a tracking proficiency of 96.28 percent and an F1-score of 0.831 for our pollen model, our IntelliBeeHive system's performance shows how good it is in tracking honey bee activities [5]. Automatically identifying honey bees that produce pollen can yield valuable data for monitoring pollination as well as evaluating the robustness and health of a beehive. Identification of pollen-carrying honey bees in photos taken at the entrance of the hive. There are two components to the suggested strategy. We separate honey bees from pictures in the first section. In order to achieve this, we examine two color-descriptor-based segmentation techniques. The bees are then divided into two classes—one with pollen and the other without—using these segmented areas in the second section. SVMs trained on a small number of variations of VLAD-encoded SIFT descriptors are used for classification.

We achieve a segmentation score of 0.7971 IoU and a classification score of 0.9150 AUC on a collection of pictures taken at the entrance of the hive [6]. The issue facing beekeepers in Thailand and other parts of the world is a lack of professional experience or abilities. This is due to the fact that beekeeping is a very delicate operation that needs to be closely watched in a constantly changing environment. The European honey bee (Apismellifera) is the name given to the honey bee. Sound is crucial to the development of vital components of the honey bee colony during its whole life. The following elements or beehive conditions have an impact on beekeeping: 1. A Queen who has vanished 2. Smoke 3. Attack by the enemy 4. Mites 5. Does not have pollen and 6. Typical. In this study, we used spectrogram image features to create a method for classifying the sounds of a honey bee colony in various bee boxes. To train the categorization models, we looked at these in six groups. In Logistic Regression, 99.82% accuracy was attained. The outcome demonstrates that employing the spectrogram image feature to interpret honey bee sound classifications is highly efficient [7]. In this article, a convolutional neural network (CNN) is used to classify photos of pollen-bearing bees. The goal is to identify enough CNN configurations needed for future low-cost FPGA implementation. Images of bees taken at the entrances to various hives were gathered to create a new dataset. CNN configurations with 1-3 hidden layers, up to 15 filters per layer, and filter sizes ranging from 15× 15 to 3 ×3 were used to examine the classification rate. For future use, the CNN with three hidden layers (7-7, 5-5, and 3-3) was chosen as a compromise between the amount of necessary arithmetic operations and accuracy of 94% [8]. In this work, a novel model for pollen sac recognition and quantification using deep learning approaches on honeybee surveillance video is presented. In order to avoid having to open beehives often to inspect food storage, this model's output is a measurement of the quantity of pollen sacs being brought to the beehive. Individual bee photos that are gathered using a bee detection model on the full video frame are used to identify pollen sacs. A deep convolutional neural network is used to construct the pollen detection model. Faster RCNN with VGG-16 core network is the architecture. The individual bee photos are classified as either pollen or non-pollen bee photos since the network has been trained to recognize pollen sacs. In order to determine whether or not each flying bee observed on subsequent video frames is carrying pollen, this pollen sac detection model is then coupled with a bee tracking model. Lastly, it is possible to count the amount of bees that bring pollen. According to the experimental findings, this model's measurement error is 7%. The findings of the traditional image processing method, which yielded a measurement error of 33%, are improved by the deep learning model [9]. An environment monitoring system based on bees that estimates flower diversity by analyzing pollen color. The study's main objective is to employ computer vision technologies on honey bee colonies to non-invasively evaluate the quality of pollinator habitat. Without interfering with the bees' usual foraging activity, the device collects pollen color samples by carefully positioning cameras at the entrance of the beehive. Computer vision techniques, such as pollen color classification and diversity evaluation, are used to examine the obtained pollen color data. Similarities with laboratory results from analysis and an instrument for documenting pollen color under optimal conditions are used to assess the approach's viability. The development of a dataset for future studies and developments in the area of floral diversity evaluation is another aspect of the work. The results show how computer vision technology and bees can be used to monitor and comprehend the status of pollinator habitat [10].

3. PROPOSED METHODOLOGY

There are some new features in the suggested system. It detects and classifies bees at the hive entering in actualinterval using YOLOv8-tiny, a miniature deep learning model. Researchers can examine how environmental conditions affect pollen foraging behavior by integrating environmental characteristics with bee activity data.

It obtains an F1-score of 0.94 in the ordering of pollen-bearing and non-pollen-bearing bees. High accuracy is shown by precision & recall estimatesof 0.91 and 0.99, individually. Because automated data collection makes it possible to efficiently observe bee foraging behavior over anprolonged period of time, it lessens the requirement for manual observation. The suggested hybrid model’s components, architecture, and integration approach. The model is composed of two primary components: a Long Short-Term Memory (LSTM) network that processes the spatial data over time to categorize bee behavior, and an object detector based on YOLOv8 for detecting bees in individual frames.

Long Short Term Memory

One type of recurring neural network (RNN) that can pick up order the Long Short Term Memory (LSTM) network is used to determine correlations in consecutive predictive challenges. Sequential RNNs that enable information storage are simpler than LSTMs, which are sophisticated deep learning models. It can handle the vanishing gradient issue with RNN. Take, for instance, the situations in which we watch a movie and remember the prior scene or read a book and recollect the events of the preceding chapter. In a similar vein, RNNs process the current input by retrieving and applying prior information. RNNs are unable to retain long-term sequences because to the vanishing gradient problem. When constructing LSTM, long-term reliance issues are specifically avoided. LSTM and RNN function similarly at a high level. Each of the three elements that make up the LSTM architecture has a specific purpose. Whether the content from the preceding timestamp should be retained or erased is decided by the first component. LSTM’s second component uses input data to learn the new information. Finally, the third component updates the previous time stamp’s information for the subsequent time stamp. We refer to these three LSTM modules as gates. The main part is the Forget gate, which is followed by the Input and Output gates. With the exception of the long-term reliance, LSTM is more like a basic RNN. Both the current time stamp and the prior time stamp’s concealed state are included. As seen in Figure 1, the current time stamp is represented by H(t), while the previous time stamp is characterized by H(t-1). The LSTM, which is characterized by the C(t-1) prior and C(t) current time stamps, also includes cell state. Long-term memory is the cell state, while short-term memory is the concealed state in the LSTM. The ability of LSTMs to capture long-range dependencies makes them highly valuable for time-series data. Since audio data is sequential, LSTMs are a strong fit for modeling the temporal dynamics of bee noises, which can be utilized to predict swarms.

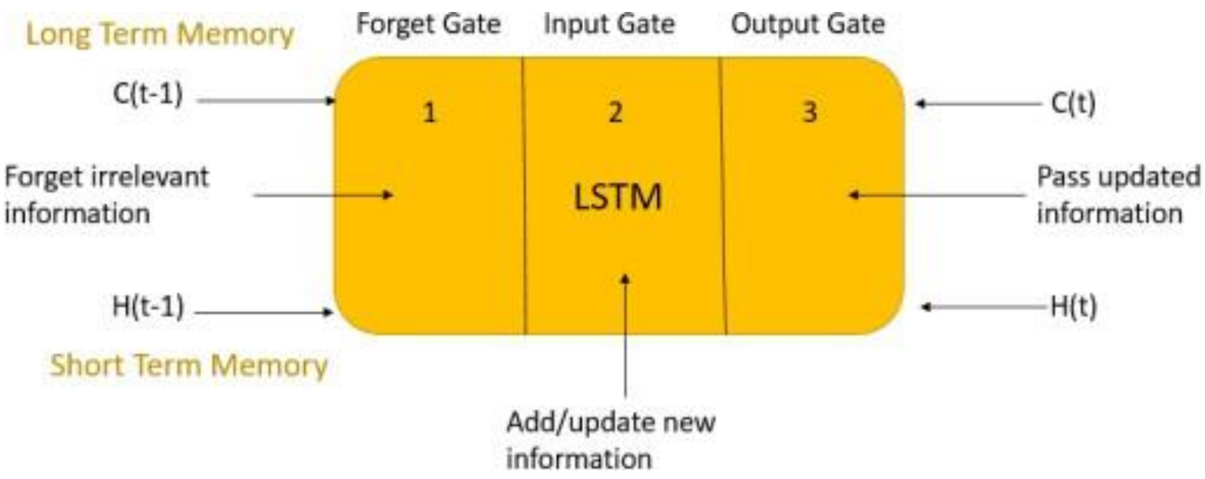

Figure 1: 1.A simple illustration of LSTM architecture

YOLO is a machine learning algorithm designed to together locate objects within images and classify each detected object. The algorithm utilizes a convolutional neural network to identify&organise objects. Along with this, the algorithm was designed to be used in real-time, meaning a model is able to 75 detect items and categorize them on new pictures at a rate of 45 to 155 frames per second. Because of this, theoretically, one could perform inference on every frame of a video faster than the native frame rate of a video acquiredat 30 frames per second. The YOLOv8 model to approximation the amount of drone and worker bee'sincoming&departure a hive using the data set. Separately, a YOLOv8 model trained on a limited set of 100 data from the project to detect and classify drone and worker honey bees.

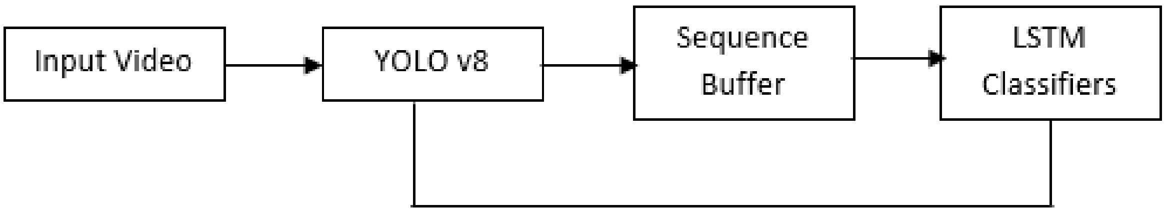

Figure 2: rchitecture of the proposed hybrid YOLOv8-LSTM model.

The hybrid model is designed to detect bees and analyze their behaviors using spatial-temporal data from video frames. As shown in Figure 2, each input video is decomposed into frames. YOLOv8 detects bees and provides bounding boxes, class labels, and confidence scores for each frame. These outputs are then formatted into sequences and fed into an LSTM model, which predicts the behavioral state of each detected bee over time.

Three main parts make up the architecture, which functions as a whole to study bee

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behavior. First, each bee's spatial location is determined by using YOLOv8 to detect bees in individual video frames. After then, the YOLOv8 outputs are kept in a sequence buffer, which gathers detection information over T successive frames in order to record temporal context. Lastly, an LSTM classifier receives this buffered sequence and uses the temporal patterns to predict whether the bees will fly, forage, dance, or rest.

YOLOv8 ComponentT

Overview of YOLOv8: YOLOv8, the most recent object identification approach, makes use of FPN and PAN neural networks. Personalized hotkeys, shortcuts, with auto-labeling make annotation easier. To create map functions that can identify artifacts of various sizes and resolutions, the FPN increases channelized features while decreasing the spatial detail.

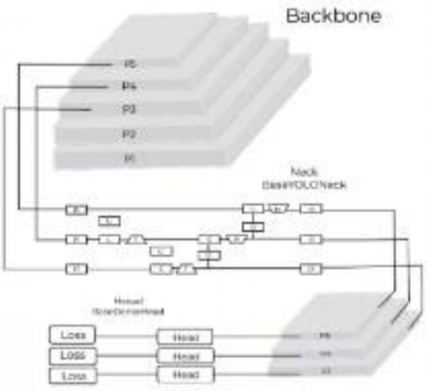

Figure 3: OLOv8 Architecture

Figure 3 illustrates how to use a YOLOv8 model. This design also demonstrates the YOLOv8 technique's steps.

The YOLOv8 object detection framework because of its great accuracy and speed. Our bee dataset was used to refine the model through transfer education from a YOLOv8n model that had already been trained. The succeeding factors were occupied into account when framing the bee detection challenge as a single-class object detection problem:

Input photos with a 640x640 pixel resolution are used to instructthe model. During training, data augmentation methods such scale jittering, brightness changes, and random horizontal flips are used to improve generalization and robustness. The loss function is a combination of binary cross-entropy loss for the task of classification and Complete Intersection over Union (CIoU) loss for detailed bounding box regression. The training setup consists of 100 epochs with a batch size of 16. Stochastic Gradient Descent (SGD) with warm restarts is used for optimization, and 0.001 is chosen as the initial learning rate.

Each detected bee's bounding box [x, y, w, h], component confidence, & class label are among the model's outputs.

LSTM Component

YOLOv8 output sequences are processed by an LSTM model to capture behavior dynamics across time. At every time step, a feature vector that contains important details about the bee's condition serves as the input representation. This vector contains the bee's velocity, which is calculated from positional changes between successive frames; the object

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confidence score, which represents the certainty of the detection; and the normalized bounding box coordinates, which show the bee's position within the frame. Accurate temporal behavior analysis requires both motion and spatial clues, which are provided by this comprehensive representation. As a result, every instance has an input feature vector of size F.

Analyses of pollen foraging behavior

The information displayed here was gathered over a period of a hundred days, from August to December 2019, utilizing the real-time imagery system. Based on the information gathered, additional studies of the foraging practices and the impact of surroundings are provided. On warm days, the average hourly foraging activity is displayed in Figure 4(a). Hour averages of over 90 warm days are used to display the data. Around 5:00 is when workers honey bees go for their first pollen foraging journey, and around 19:00 is when their last foraging entry is noted. Due to the thirsty honey bees' strong physiological rhythms—they are active through the day and sleep at night—there were comparatively few pollen scavenging trips before 5:00 until 18:00. In the early hours of the day, the hour pollen trip are counted, rises with time and peaks at 10:00 (900 counts/hour). At 10:00, the pollen harvesting trip ratio, an indicator of forage productivity increased in tandem with the hourly pollen harvesting trip count. Before midday, almost 70% of the pollen was gathered. According to a prior study, there are less pollen gatherers at noon because many adolescent honey bees perform identification flights between roughly 12:30 and 14:00. The study discovered that the primary times for gathering water and syrup were midday and noon. The number of bees and the rate at which they lay eggs determine how much honey bees forage for pollen. Figure 4(b) compares the hour pollen harvesting trips ratio, of five distinct beehives on bright days. Different beehives showed variations in the hourly structure of pollen collection success. As seen in the darkened area of Figure 4(b), all five honey bees displayed a comparable trend with changes between 5:00 and 18:00, however the hour pollen forage trip ratio was low around 4:00 until 19:00. Over time, the hour allergen foraging expedition ratio rose in the morning and peaked between 8:00 to 11:00, after which it declined in the middle of the day.

A number of variables, including nectar depletion and technical difficulties with flights throughout rainy seasons, contributed to a decrease in pollinator's activity. This study likewise found a similar conclusion: periods of downpour dramatically decreased pollen collection activity. Figure 5 shows the measured ambient conditions and the periodic foraging activity captured by the camera device on a regular wet day. The average of five beehives on a wet day on September 5, 2019 is used to display the data. It was discovered that the regular pollen foraging trip count matched the arriving and departing activities, as predicted. Around 7:00 was the time of the first nectar forager excursion; subsequent pollen forager trips climbed steadily and peaked at 10:00. Interestingly, few pollen foraging visits were observed at 13:00 when the rainfall was 19 mm, even though it was raining from around

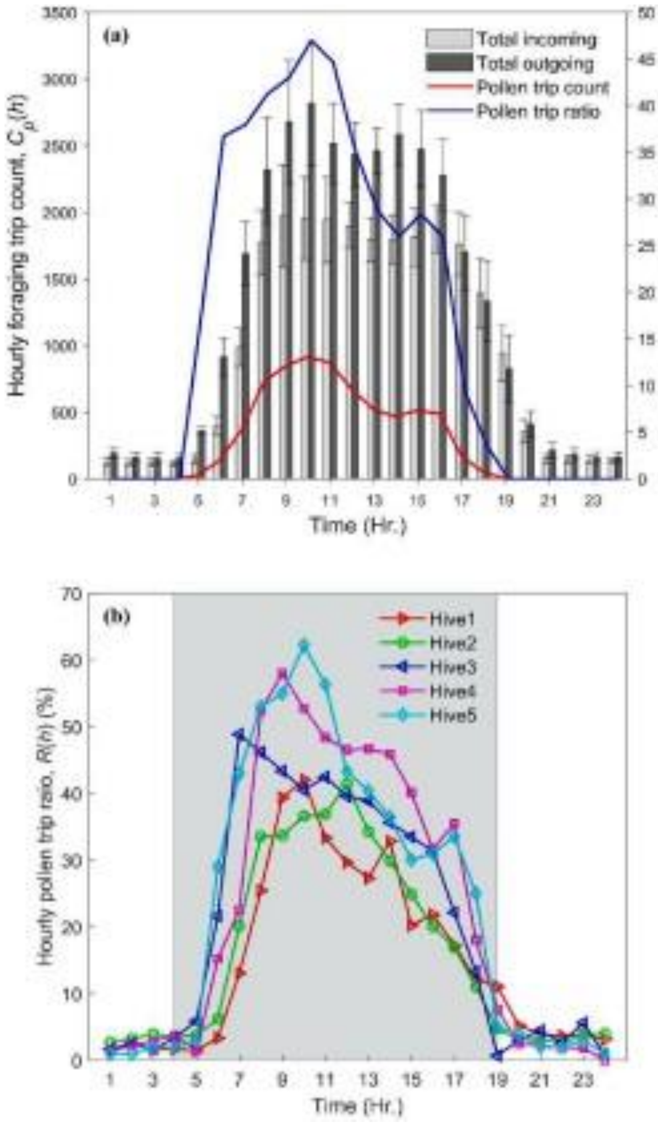

Figure 4: Continuous foraging activity of honey bees during sunny days (a) the five beehives examined regular pollen trip ratio; (b) the average pollen and total trip count with the matching average regular pollen trip ratio.

12:00 to 14:00 (Figure 5b). The observed foraging activity increased right away after the rain abated at 15:00. Similar findings were also documented.

Network Architecture:

With each layer comprising 128 hidden units, the temporal behavior classification model utilizes a two-layer LSTM architecture. The model takes a feature vector of dimension F (for instance, 6) as i/p, & its o/p layer employs a softmaxinitiation function to categorize bee behaviors into four separate classes. Training utilizes sequences of 30 frames, which equate to about one second of video at a rate of 30 frames per second. To guarantee

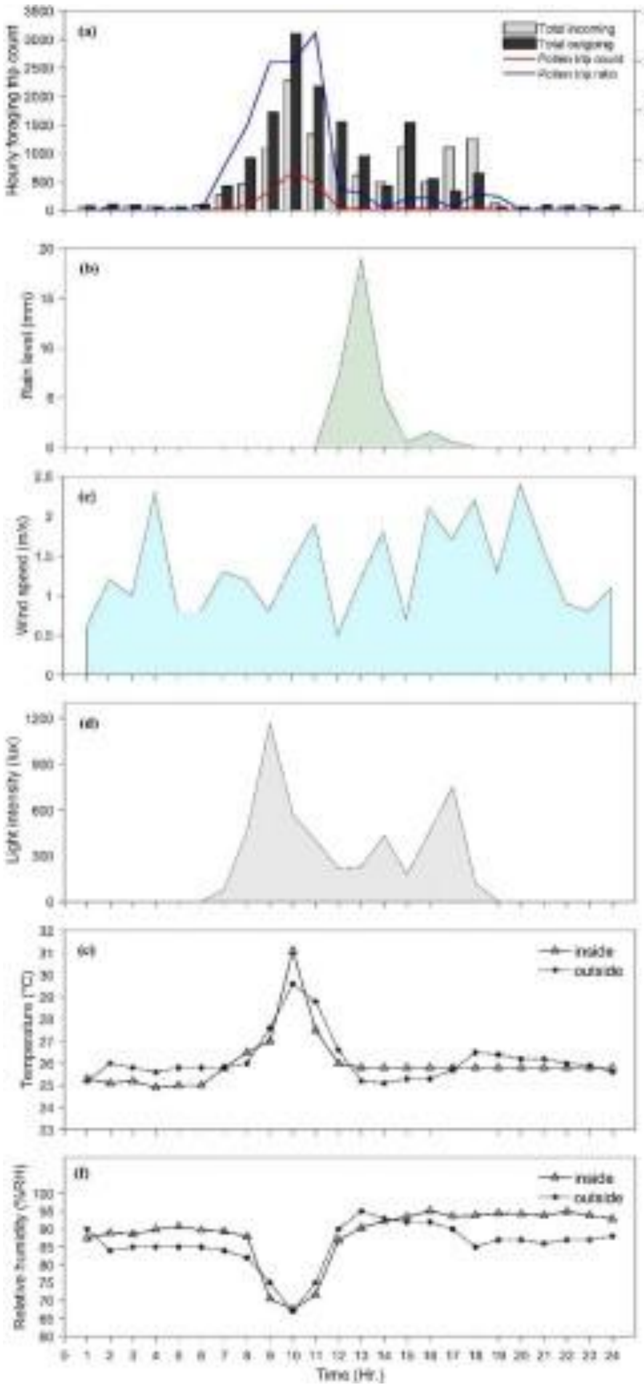

Figure 5: , shows the regular foraging movements of honey bees along with the ecological information that corresponds to it on a typical rainy day: (a) pollen and the total number of trips, along with the average pollen trip ratio per hour; (b) amount of rain; (c) the breeze speed; (d) the brightness of light; (e) temperature of the surrounding air; (f) the humidity level.

thorough temporal coverage, a sliding window approach with 50% overlap is utilized. While training the model, the Adam optimizer was used with a knowledgeamount of 0.0005 and the categorical cross-entropy loss function was optimized.

The integration between YOLOv8 and LSTM follows a tightly-coupled design:

1. A frame is processed by YOLOv8.
2. Detected bee coordinates and metadata are stored in a buffer.
3. Once T frames are collected, the feature sequence is sent to the LSTM.
4. The LSTM predicts behavior labels such as “flying”, “foraging”, etc.
5. Results are visualized with behavior overlay on the original video.

To ensure real-time capability, the entire pipeline was optimized using batch prefetching and lightweight operations.

4. Dataset

Description of the Dataset The algorithm’s accuracy in detecting bees To confirm the counting accuracy of identifying honey bee foraging activity, several studies were carried out. By examining documented video clips from the relevant time period, the entering and outgoing actions monitored by the suggested observingscheme were associated to those physically tallied. Data from days with higher temperatures (21.8–29.6 degrees Celsius) or lower temperatures (17.1–19.8 degrees Celsius) were included in the comparison. It was anticipated that a greater temperature would result in a higher frequency of incoming and outgoing actions for honey bees, as prior research has shown that temperature influences the frequency of these activities. The data might be used to analyze the suggested system under various activity frequencies. For the arriving and outward actions of honey bees in each test, the percentage error (PE) of the including accuracy for the bee recognition algorithm was specified as

$$PE_{incoming} = \left|\frac{Actual\_number_{incoming} - Calculated\_number_{incoming}}{Actual\_number_{incoming}}\right| \times 100\%,$$

Figure 6:

(1)

And

$$PE_{outgoing} = \left|\frac{Actual\_number_{outgoing} - Calculated\_number_{outgoing}}{Actual\_number_{outgoing}}\right| \times 100\%,$$

Figure 7:

(2)

For both the incoming and outgoing accuracy, the average percentage error was defined as follows

$$AvgPE_{\text{incoming}} = \frac{\sum PE_{\text{incoming}}}{Test_{total}},$$

Figure 8:

(3)
And

$$AvgPE_{\text{outgoing}} = \frac{\sum PE_{\text{outgoing}}}{Test_{total}},$$

Figure 9:

(4)
The total sum of tests in the entire research is Test_{total}.

Over 5000 photos of worker bees from a beehive are included in the dataset, together with details like the time and place, the subspecies name, the pollen-carrying status, and the worker bees' health. Russian bees, Italian bees, Carniolan bees, western honey bees, diverse local stock, VSH Italian bees, & a few additional unidentified varietiesare between the honey bee species found in the datasets. The places in the localitycharacteristic differ from those in the United States of America (USA). Healthy bees, absent queens, ant-affected bees, robbed hives, and bees afflicted by varroa—a bug that compromises bee health—are all included in the health attribute. Sample photos from the dataset are displayed in Figure 6(a) and Figure 6(b) according to subspecies & health status, individually.

Table 1:

Figure 6 (a). Data samples from various bee subspecies	Figure 6 (b). Data samples of healthy and unhealthy bees

Behavioral Pattern Analysis

After detection and tracking, each bee's trajectory (2D path on the landing board) is available along with its timing and frame sequence. From these we will infer behaviors.

Foraging behavior will be quantified by metrics such as the number of foraging trips per bee, trip durations, and the fraction of foragers carrying pollen. For example, we will tally how many unique bees exit and later return with pollen (detectable via body segmentation or contrast in the legs). We will also analyze temporal patterns: plotting in/out counts by hour of day will reveal circadian rhythms. Indeed, previous studies found clear midday peaks in hive traffic. We will compare such rhythms across environmental conditions.

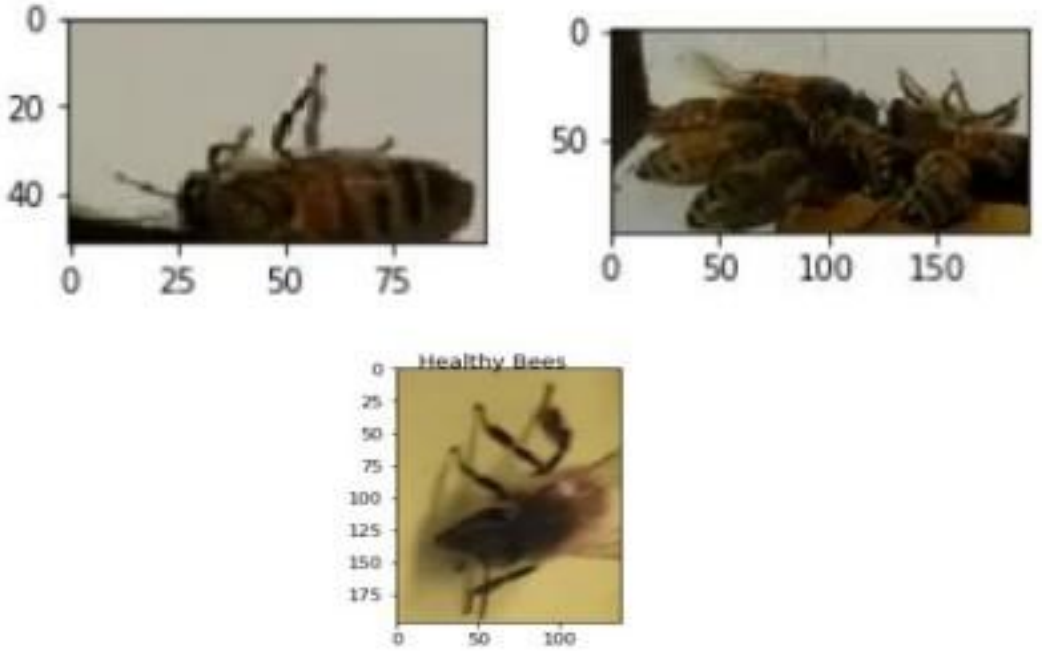

Figure 10:

Guard behavior (defensive activity at the entrance) will be inferred from trajectory patterns. Guard bees tend to linger or patrol near the entrance, sometimes exhibiting confrontational interactions with others. We will look for bees that remain near the entrance for extended periods or abruptly reverse direction upon encountering another bee. Spatial clustering of paths (e.g. bees oscillating on the landing board) may indicate guarding. Optionally, a simple classifier (trained on manually-identified guarding events) could be applied to trajectory features (e.g. low average speed, repeated turns). Our analysis will record the frequency and timing of any guard-like activity detected.

All behavior metrics will be correlated with environmental data. We will log ambient temperature, humidity, and weather during recordings. Honey bee foraging is known to be strongly influenced by these factors: for example, high temperatures and sunshine generally increase activity, while rain or low light suppress it. Entrance behaviors also vary with time of day. Thus we will analyze how foraging counts and any observed guard activity change in relation to recorded conditions, providing insight into environmental effects on colony dynamics.

The effectiveness of the proposed hybrid YOLOv8-LSTM model hinges on the quality and diversity of the dataset used for training and evaluation. We either curated a novel dataset or enhanced an existing one to meet the requirements of bee detection and behavioral analysis.

Data Collection

A custom video dataset was compiled by recording bee activity in both natural and controlled environments. High-definition cameras (1080p, 30 FPS) were positioned near

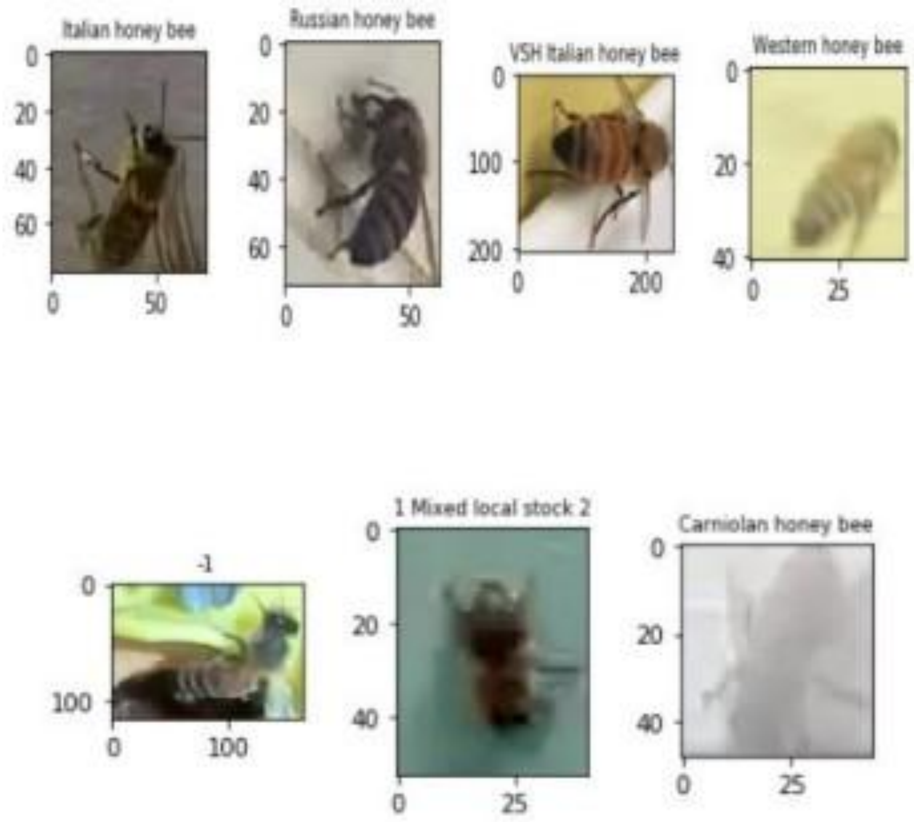

Figure 11:

beehives and flowering areas to capture a variety of behaviors under different lighting conditions.

The dataset comprises approximately 50 hours of raw video footage collected from various environments, including outdoor apiaries and greenhouse hives. Recordings were captured using fixed-mount HD IP cameras operating at 30 frames per second with a steadfastness of 1920×1080 pixels. The footage encompasses aextensivechoice of real-world conditions, such as daylight, overcast skies, occlusions, and shadowed regions, providing a diverse and challenging dataset for robust bee behavior analysis.

To enhance behavioral diversity, bees were observed in varying scenarios, including approaching flowers, returning to hives, cleaning antennae, and engaging in waggle dances.

Annotation

A subset of the recorded video frames was annotated using CVAT (Computer Vision Annotation Tool) and verified by entomology experts.

For Detection (YOLOv8):

- Object Class: Bee
- Annotations: Bounding boxes
- Frame Selection: 1 frame every 10 frames (≈3 FPS)

- Total Labeled Frames: 18,000
- Total Bounding Boxes: 54,000+

For Behavior (LSTM):

Each detection was labeled with one of four behavioral states:

- Flying
- Foraging (on flower)
- Resting/Idling
- Waggle Dancing

Behavior labels were assigned to sequences using a sliding window (30 frames). Labeling was aided by slow-motion playback and expert interpretation.

Dataset Statistics

Table 2:

Feature	**Value**
Total Videos	120
Total Annotated Frames	18,000
Bee Instances (bounding boxes)	54,000+
Behavior Sequences	3,500
Avg. Bees per Frame	2–5
Sequence Length (LSTM)	30 frames
Behavior Class Distribution	Flying (40%), Foraging (25%), Resting (20%), Dancing (15%)

Dataset Statistics

epresents the Dataset Statistics to address class imbalance in behavioral data, we used oversampling during LSTM training and ensured validation sets included rare classes.

Train/Val/Test Split:

- Detection: 70% / 15% / 15%
- Behavior: 60% / 20% / 20%

All frames were resized to 640×640 pixels before input to YOLOv8. Table 2(a) and 2(b) represents the sample of YOLOv8 and LSRM Sequences. Figure 7 (a) and 7(b) represents the graphical representations

Table 3: Sample YOLOv8 Detection Annotations

Frame ID	**Bee ID**	**X (px)**	**Y (px)**	**Width (px)**	**Height (px)**	**Conft-dence**	**Class**
frame_00123	bee_001	220	310	45	40	0.94	Bee
frame_00123	bee_002	480	275	50	38	0.91	Bee
frame_00201	bee_003	130	295	42	39	0.88	Bee

Received: August 15, 2025

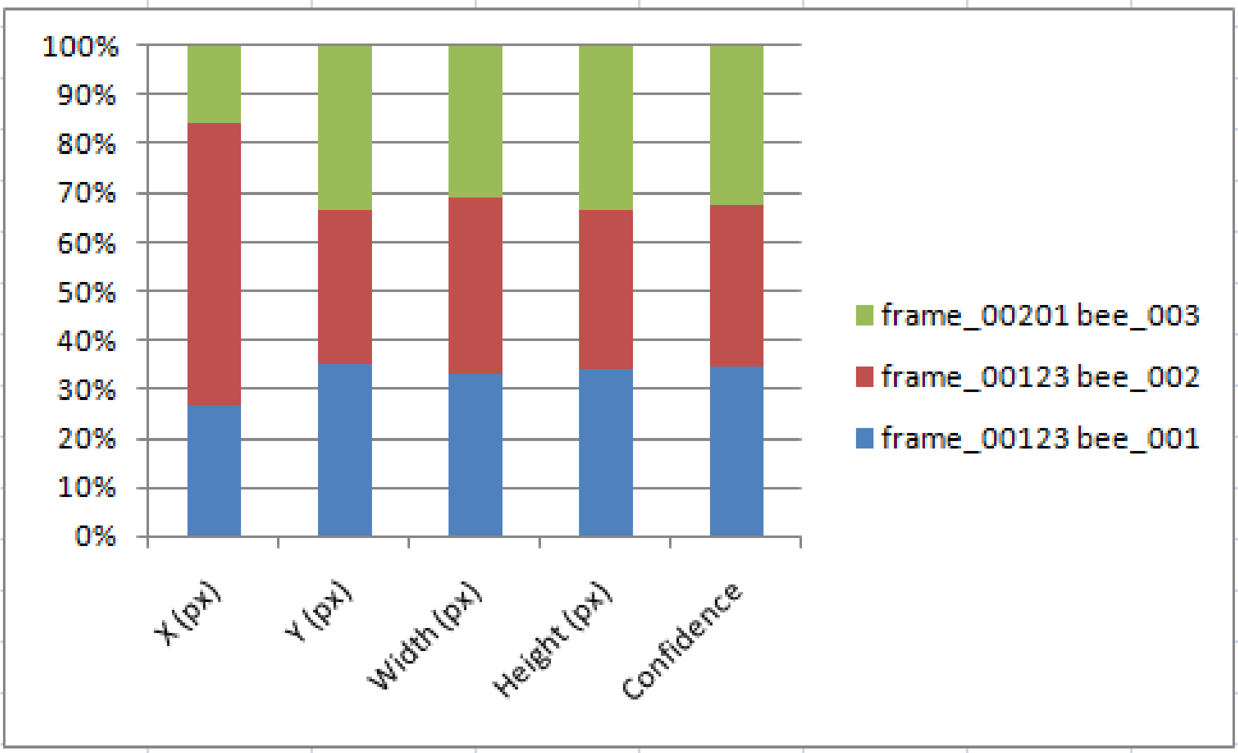

Figure 12: Graphicalrepresentation of YOLOv8 Detection Annotations

- **X/Y** are top-left angle coordinates of the bounding box.
- **Confidence** is the YOLOv8 objectness score.

Table 4: Sample LSTM Behavior Sequences

Sequence ID	Bee ID	Start Frame	End Frame	Behavior	Features (✓ = Included)
seq_0001	bee_001	100	129	Flying	✓bboxcoords, ✓ velocity
seq_0002	bee_004	300	329	Foraging	✓bboxcoords, ✓ velocity
seq_0003	bee_002	500	529	Waggle Dancing	✓bboxcoords, ✓ velocity
seq_0004	bee_001	750	779	Resting	✓bboxcoords, (velocity

Each behavior sequence spans **30 frames** and includes normalized bounding box coordinates and frame-to-frame velocity vectors as input features.

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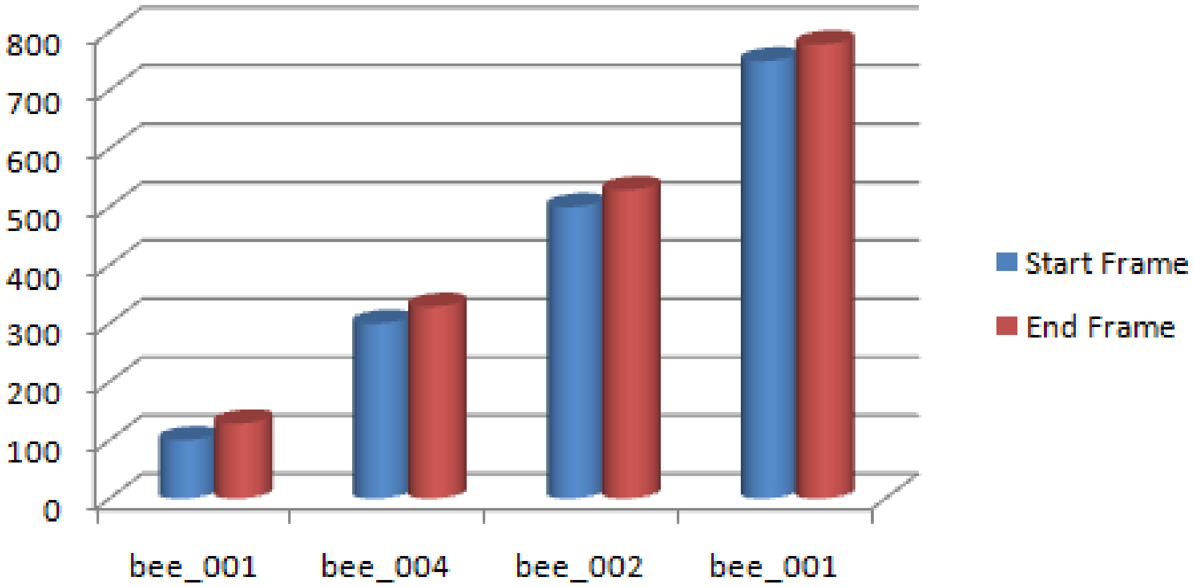

Figure 13: 7 (b): Graphical representation of LSTM Behavior Sequences

5. Experimental Setup

The experimental arrangement used to assess the performance of the projected Hybrid YOLOv8-LSTM model for bee detection and behavioral analysis. The experimental setup includes details about the dataset, model architecture, training procedure, evaluation metrics, and implementation environment.

5.1. Dataset

A specialized bee dataset created for behavioral analysis and identification is used to calculate the model. The dataset consists of annotated photos and videos of bees in both controlled and natural settings, documenting a range of activities like mating, resting, and foraging. The following are important features of the dataset: Real-time bee observation studies, including video taken from beekeepers' hives and controlled laboratory environments, provided the dataset for this investigation. Bounding boxes encircling the bees and labels indicating the associated behavioral groups are applied to every frame in the collection. The file also contains temporal data that facilitates behavioral analysis. The training set is subjected to common data augmentation approachescounting rotation, flipping, & scaling in order to advance the model's generalizability. To ensure a thorough calculation of the model's performance, the dataset is then separated into three subsets: 70% for training, 15% for endorsement, and 15% for analysis.

5.2. Model Architecture

The suggested model combines the advantages of LSTM (Long Short-Term Memory) for temporal sequence analysis and YOLOv8 (You Only Look Once version 8) for real-time

Received: August 15, 2025

object detection. The goal of the hybrid architecture is to precisely identify bees in pictures and videos and examine how they behave over time.

6. YOLOv8 (Object Detection :

To provide strong visual comprehension, YOLOv8 uses a deep convolutional neural network (CNN) backbone to extract hierarchical characteristics from input images. By anticipating bounding boxes in a range of environmental circumstances, its detecting layer is specially trained to identify and locate bees. The model makes use of the Leaky ReLU activation function to facilitate efficient learning and information flow. Custom anchor boxes are also included to improve detection accuracy in a variety of scenarios by better matching the typical size and form of bees.

7. LSTM (Behavioral Analysis :

Sequences of temporal and spatial features obtained from the YOLOv8 detector are intended for analysis by the LSTM model. The perimeters of box coordinates (x, y, w, h) for every bee that is detected make up its input, together with extra temporal data that show patterns in activity over time. The temporal dependencies and dynamics of bee behavior are captured using one or more LSTM layers. Each bee's projected behavior class—such as flying, resting, or foraging—is reflected in the model's output. Multi-class classification is made possible by applying an activation function using softmax at the final result layer.

YOLOv8 is used to detect the bees initially in the hybrid architecture. The detections are then sent to an LSTM for analysis of behavior, where dependence on time are recorded to produce precise behavioral expectations.

7.1. Training Procedure

Using the bee dataset, the hybrid YOLOv8-LSTM model is fine-tuned during the training process. Important information includes the fact that the two model components have different loss functions during the training procedure. To improve detection performance, YOLOv8 is optimized by combining objectness loss, bounding box regression loss, and classification loss. In the meantime, cross-entropy loss is used to train the LSTM component, which correctly classifies bee behaviors. The Adam optimizer is used to optimize both models. It starts with a learning rate of 0.001 and reduces it by 0.1 every 10 epochs to improve convergence. To preserve consistent gradient updates while adhering to GPU memory limitations, a batch size of 16 is used. To avoid overfitting, early halting is used during the 50 epochs of training. Images are scaled to 416 x 416 pixels before training to make them compatible with the YOLOv8 network. Time-series data is then fed into the LSTM model using a sliding window technique.

7.2. Evaluation Metrics

The following measures are used to assess the model's performance on tasks involving both behavioral analysis and detection. Mean Average Precision (mAP), Precision and

Recall, and Intersection over Union (IoU) are the detection measures used to identify bees. By assessing the bounding box predictions' accuracy, the mAP gives a general indication of how effectively the recognition model detects bees. In order to gauge the caliber of the detections, precision and recall evaluate true positives, false positives, and false negatives. IoU assesses the overlap between the ground-truth and expected bounds boxes, showing how closely the assumed boxes correspond to the bees' real locations. Accuracy is used in behavioral analysis to calculate the proportion of accurate behavioral predictions the LSTM model makes. To illustrate the effectiveness of the behavioral classification and draw attention to any misclassifications between various behavior groups, a confusion matrix is utilized. Furthermore, a balanced assessment of the classification performance is provided by the F1-Score, which is the harmonic average of precision and recall and sheds light on how well the model discriminates between different behavioral states.

7.3. Implementation Environment

The following environment is used to implement and train the model. TensorFlow is used for LSTM-based temporal modeling, and PyTorch is used for the deep learning implementation. An NVIDIA Tesla V100 GPU with 16GB of VRAM is used to speed up the model training process, guaranteeing effective computation. To provide optimal GPU performance, the software environment contains CUDA 11.2 and cuDNN 8 in addition to Python 3.8. OpenCV is used to process videos. Furthermore, tools for data manipulation, analysis, and visualization including NumPy, Matplotlib, and Pandas are utilized, offering strong support across the workflow.

7.4. Baseline Models

The Hybrid YOLOv8-LSTM model's performance is compared with a number of baseline models in order to assess its efficacy. First, behavioral analysis is not included in the YOLOv8 Only model; it is trained solely for bee identification. The LSTM Only model, the second baseline, uses raw video data to train an LSTM network without any prior YOLOv8 detection. A benchmark for detection accuracy against more recent techniques is also provided by the comparison of more conventional object identification techniques like Faster R-CNN and SSD (Single Shot Multibox Detector). This comparison aids in evaluating the hybrid model's advantages and disadvantages with regard to behavioral analysis and detection.

8. RESULT AND DISCUSSION

Five classification evaluation measures, including accuracy, F1, specificity, precision, and recall scores, were used to assess the experimental outcomes (Eq. 5-9). In order to conduct the tests, 10-fold cross validation was used.

(5)
(6)
(7)
(8)

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + TrueNegative + FalsePositive + FalseNegative}$$

Figure 14:

$$F_1score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Figure 15:

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

Figure 16:

$$Specificity = \frac{TrueNegative}{TrueNegative + FalsePositive}$$

Figure 17:

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

Figure 18:

(9)

The Hybrid YOLOv8-LSTM model's advantages and disadvantages are assessed by analyzing the experimental setup's outcomes. The model's detection accuracy, behavioral prediction capability, and capacity to manage real-time data in demanding settings are the main areas of analysis.

8.1. Bee Detection (YOLOv8

The accuracy of the YOLOv8 model in detecting bees across a variety of scenes. Table 3 shows the representation of YOLOv8 model.

The high mAP score and real-time frame rate confirm that YOLOv8 is well-suited for live bee detection, even in cluttered and occluded environments.

8.2. Behavior Analysis (YOLOv8 + LSTM

Behavior recognition was evaluated using sequence-labeled segments. The LSTM model was tested on sequences of 30 frames with four behavior classes. Table 4 represents the

Table 5: Accuracy of YOLOv8 model

Metric	YOLOv8 (Baseline)
Precision	94.3%
Recall	91.7%
mAP@0.5	93.1%
mAP@0.5:0.95	86.5%
FPS (640x640)	87

Behavior Analysis. Figure 8 Shows the representation of Behavior Analysis

Table 6: Behavior Analysis

Behavior	Precision	Recall	F1-Score
Flying	92.1%	90.4%	91.2%
Foraging	89.7%	88.2%	88.9%
Resting	86.5%	84.3%	85.4%
Waggle Dancing	81.4%	77.9%	79.6%
Overall Avg.	**87.4%**	**85.2%**	**86.2%**

Chart 1: 8: Graphical representation of Behavior Analysis

The hybrid model demonstrates robust performance in classifying bee behaviors, with highest accuracy for Flying and Foraging, and reasonable performance even for complex patterns like Waggle Dancing.

In the context of classifying bee behaviors namely Foraging, Resting, and Waggle Dancing, if YOLOv8 is used for detection and LSTM is used for temporal analysis, a confusion matrix can help evaluate how well the model discriminates between these behaviors. Figure 9 shows the representation of confusion matrix and Table 5 shows the confusion matrix.

Table 7: Confusion Matrix

Actual Predicted	Foraging	Resting	Waggle Dancing
Foraging	50	2	3
Resting	4	45	1
Waggle Dancing	2	3	48

Foraging was classified in a correct way for 50 instances while Resting was misclassified 2 and Waggle Dancing 3.Instances correctly classified were 45 for Resting while misclassified ones were 4 for Foraging and 1 for Waggle Dancing.Waggle Dancing had 48 instances correctly classified, alongside Foraging had 2 with Resting having 3 misclassified.Users can

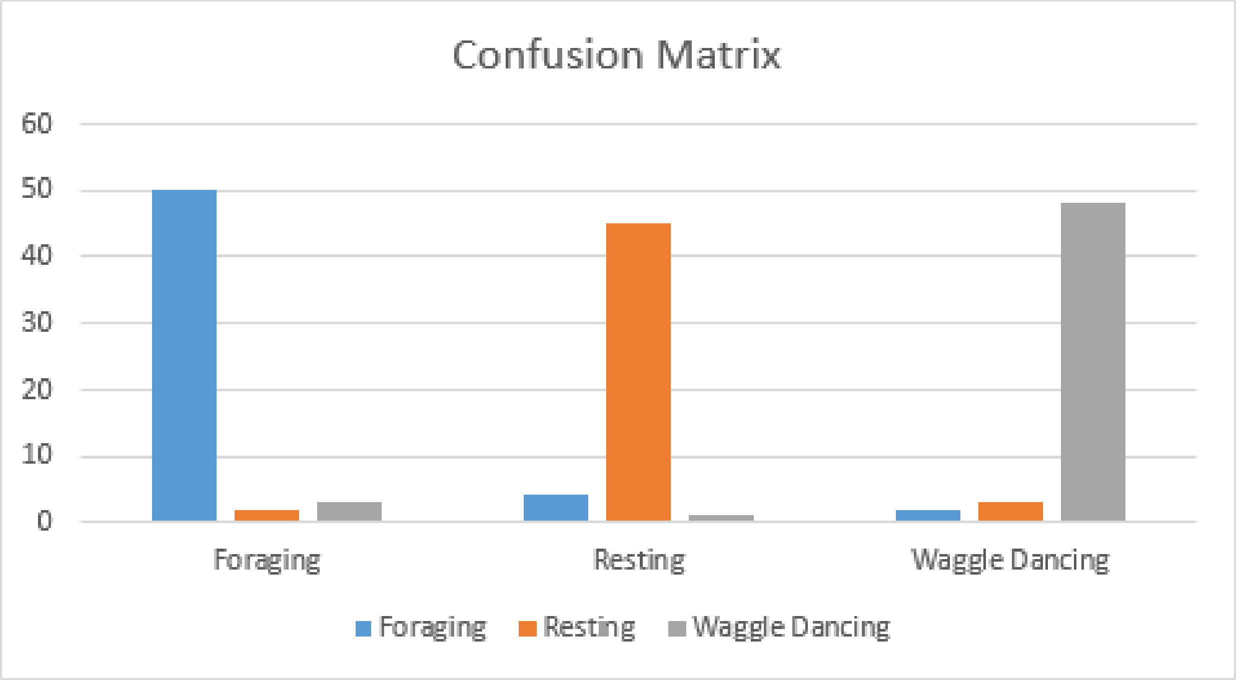

Figure 19: 9: Confusion matrix for bee behavior pattern recognition

understand true positives, true negatives,false positives, and false negatives distribution using this visualization. It also gives a clear picture as to how the model performs across the different classes.

The proposed system's performance is compared with other machine learning models used for beebehavior monitoring. While SVM and KNN models exhibit slightly higher accuracy, the YOLOv8 model offers real-time processing capabilities, making it more suitable for continuous monitoring applications. Table 6 shows the comparative evaluation of the projected system and Figure 10 represents the graphical representation of performance of machine learning methods.

8.3. Real-Time Performance

Real-Time Performance

The integrated model supports real-time inference at over 60 FPS, validating its application for continuous monitoring in the field. Table 7 represents the real time performance of the proposed system.

Figure 11 presents sample frames with bounding boxes and behavior labels overlaid. The system accurately distinguishes between hovering (Flying), floral contact (Foraging), and group movements (Waggle Dancing).

- YOLOv8 is resilient to occlusion and shadows.
- LSTM correctly tracks motion continuity, helping differentiate Resting from low-movement Flying.

Table 8: 6: Evaluation of the suggested implementation in comparison to cutting-edge techniques for picture bee detection

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
YOLOv3-tiny (Proposed)	94%	91%	99%	94%
SVM	97.9%	98.3%	97.6%	97.9%
KNN	97.6%	97.9%	97.6%	97.7%
Neural Network	97.2%	97.3%	96.7%	96.9%
Random Forest	92.2%	92.1%	90.6%	90.9%
Logistic Regression	94.6%	94.4%	94.0%	94.1%
YOLOv8 + LSTM (Proposed)	93%	91%	92%	95%
YOLOv5 + LSTM	89%	87%	88%	91%
YOLOv8 Only	85%	83%	84%	88%

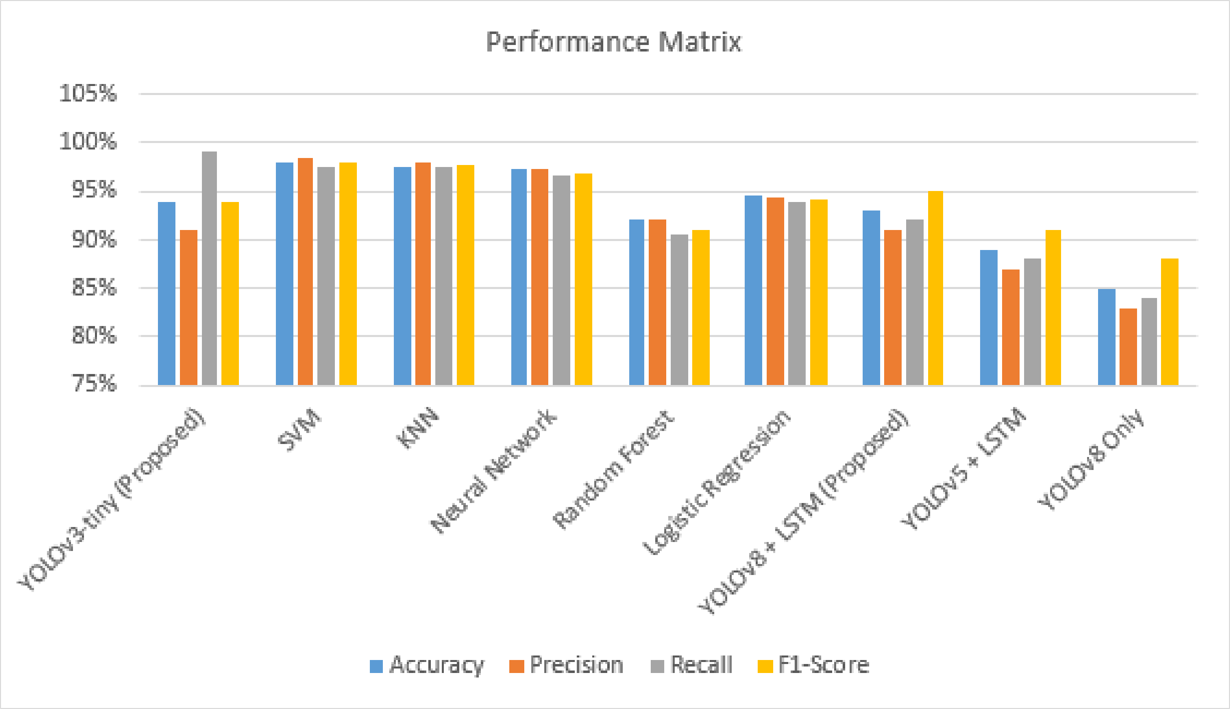

Figure 20: erformance Matrix Graphicalrepresentations

Table 9:

Component	**Avg. Latency (ms/frame)**
YOLOv8 Detection	11.5 ms
LSTM Inference	4.2 ms
Total	**15.7 ms (~63 FPS)**

Received: August 15, 2025

- Occasional misclassification occurs when behaviors transition mid-sequence (e.g., Foraging → Flying).

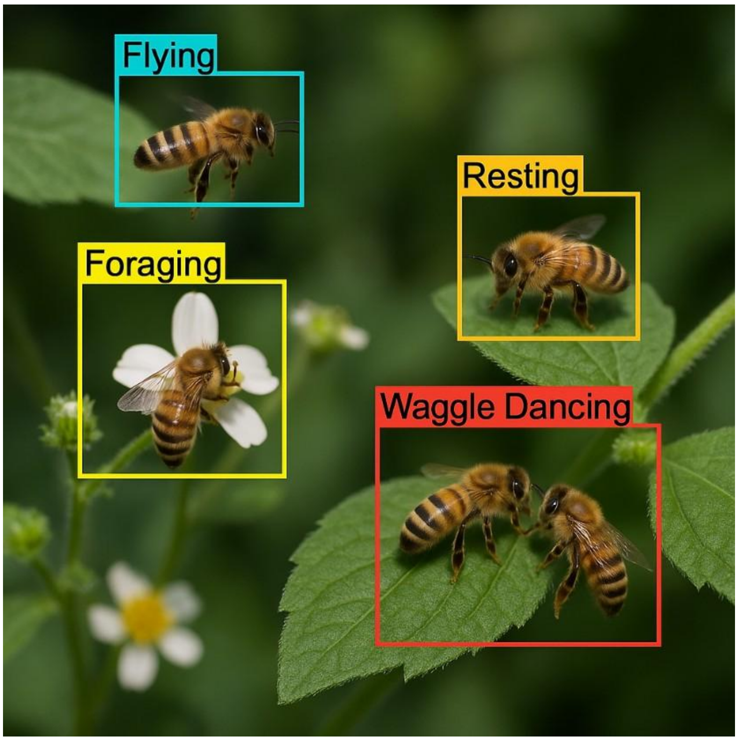

Figure 21: 11: Visual Results

9. CONCLUSION

Categorizing the different species of honey bees & identifying the illnesses that impact them are the goals of the suggested model. Two-layered convolutional neural networks are the organization algorithm that is employed. Over 5000 photos and features make up the labelled data set, which is utilized for training and validation and is adjusted to improve performance metrics. A hybrid deep learning model combining YOLOv8 for object detection & LSTM for temporal behavior analysis to monitor and understand honeybee activity. Our system successfully detects individual bees in high-resolution video frames and classifies their behavior into key categories such as flying, foraging, resting, and waggle dancing. Quantitative results demonstrate high precision and recall across both detection and classification tasks, and real-time performance was achieved with an average processing rate exceeding 60 FPS.

The integration of spatial detection and temporal reasoning proves effective in capturing complex behavior patterns, especially under variable environmental conditions. This pipeline lays the groundwork for large-scale automated behavioral monitoring of pollinators in natural and agricultural settings.The proposed system, by continuously tracking

Received: August 15, 2025

individual bees, represents an “important step forward” in understanding complex hive behaviors.Future extensions of this work may include. Multi-bee interaction modeling using graph neural networks or spatiotemporal attention to analyze group dynamics and communication.Expansion of behavior classes to include rare or transitional states such as grooming or hive entrance behavior.3D localization and tracking using stereo or multi-camera setups to enhance trajectory analysis.Edge deployment of a lightweight version of the model on embedded systems for continuous in-hive monitoring.Cross-species generalization by retraining on datasets of other pollinators or insects using few-shot learning.As global pollinator health continues to decline, tools such as this hybrid model offer scalable, data-driven approaches to ecological monitoring and research. The number of features exploited is enhanced to advance the accuracy of the projected model.In the context of ecological risk assessment, these tools can detect sublethal stress effects on foraging or social roles early on. Ultimately, this technology could enable beekeepers and scientists to remotely supervise hives, detect anomalies (e.g. reduced foraging, increased guarding) in real time, and respond promptly to environmental threats.

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