BEE-HELP: A Novel and Efficient Early Warning System for Beehive Health Using Statistical Analysis of Beehive Weight Data

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Abstract

Colony Collapse Disorder (CCD) poses a significant threat to global agriculture due to its impact on honeybee populations, which are essential pollinators. In response, we developed an early warning system that leverages a technological platform to continuously monitor beehive health. Our solution 'BEE-HELP' integrates an array of ruggedized weight sensors and environmental monitors, transmitting real-time data wirelessly to a cloud-based infrastructure, with our system having been running for over a year with minimal maintenance or interruptions. As part of our research, we installed the monitoring system and collected data in the field at a local bee farm. The system synchronously samples sensor data every hour, forming a multivariate time series used to (a) trigger alerts when measurements deviate from predefined thresholds indicative of healthy hive behavior, and (b) predict future hive health trends using historical data. A key finding from our analysis is that approximately 150-200 hours before a hive collapse, weight data exhibits a significant increase in standard deviation. This insight enabled the creation of an algorithm that processes raw data to identify the transition from healthy to unhealthy hive states. By applying statistical techniques, including inverse F distributions and F-tests, we refined our predictive model, enhancing its accuracy to 77.8% (95% CI). Notably, through field testing on 12 monitored hives, we successfully prevented the collapse of 3 hives by identifying early indicators of hive health decline. This early intervention, facilitated by our algorithm, demonstrated tangible benefits for beekeepers, validating the system's practical utility. With an implementation cost of $150 per hive and projected savings of $200-250 per prevented collapse, the system offers a favorable cost-benefit ratio. As we continue to scale the system, it holds significant potential to become a reliable tool for promoting sustainable agricultural practices. Our ongoing collaboration with sensor manufacturers aims to make this monitoring technology widely accessible to beekeepers. Ultimately, by providing an early warning of hive distress, this system has the potential to mitigate CCD, support bee colony preservation, and promote agricultural sustainability. The simplicity and effectiveness of this predictive algorithm underscores its value as a practical tool for beekeepers.

1 Introduction

Honeybees (Apis mellifera) play a critical role in global agriculture, with bee-pollinated crops contributing to approximately one-third of the total human dietary supply. Their value to crop production is significant, with estimates in the U.S. alone reaching $15 billion annually. However, honeybee populations have been declining at alarming rates, largely due to Colony Collapse Disorder (CCD). CCD is marked by the sudden disappearance of worker bees, leaving behind a queen and brood, with a colony unable to sustain itself. This phenomenon threatens food security and biodiversity. Although various factors—pesticides, pathogens, and habitat loss—are linked to CCD, the precise cause remains unclear.

Recent studies estimate global economic losses from CCD at $5.7 billion annually, highlighting the urgent need for early detection systems. While existing monitoring solutions often rely on complex sensor arrays measuring multiple parameters, we hypothesized that weight data alone, properly analyzed, could provide sufficient early warning of colony decline. This approach offers significant advantages in terms of cost, maintenance, and scalability.

To address this limitation, we established our own bee farms for primary data collection. One of our farms, located off-grid and outside city limits, posed a unique challenge for real-time hive monitoring. To overcome this, we developed a solar-powered monitoring system capable of wirelessly collecting and transmitting data from an array of weight and temperature sensors to the cloud. This setup enabled continuous monitoring and daily reporting on hive health, allowing us to collect the detailed, natural-condition data needed for our research.

By tracking key variables such as weight and temperature through time-series analysis, it is possible to detect patterns that may signal the onset of collapse. In this study, we present an early warning system that uses multivariate sensor data to monitor hive health. Our system analyzes weight fluctuations and other environmental factors, using statistical models to detect abnormal changes. This approach offers beekeepers the ability to intervene before hive collapse occurs, contributing to the broader effort to mitigate CCD and support bee colony preservation.

2 Literature Review

Precision beekeeping is an apiary management strategy which involves monitoring bee hives to minimize the use of resources and maximize productivity of bees. Alleri [1] analyzed 65 articles, each highlighting particular internal parameters such as internal temperature, relative humidity, flight activity, and sound. One of the key findings relates beehive health to weight of the hive, which is the main factor behind our own research. Alleri found that increase in beehive weight indicates honey production and population expansion while a decrease in weight indicates consumption of honey, swarming, or "mortality events." Danieli [2] also analyzed the pros and cons behind precision beekeeping, and found that the use of advanced sensors and machine learning provides accurate information about beehives, allowing timely intervention when hive health declines to disease or pests. However, one of the cons behind precision beekeeping is its high costs which prevents it from being scaled to a large level. Zaman [3] analyzed studies regarding hive monitoring sensor technology and reevaluated those studies using an Operational, Investigative, and Predictive (OIP) monitoring framework. This OIP framework found gaps in hive monitoring research and technology. An example of such gaps includes the lack of data on Stingless bees and Asian honeybees, preventing investigative and operational monitoring from taking place. Robustillo [4] used static and dynamic vector auto regressive (VAR) models and linear and nonlinear regression models in order to predict internal beehive variables such as temperature, relative humidity, and weight. The models were compared using a 100-fold-cross-validation adjusted for time series, and were tested on datasets procured from [1]. It was found that the VAR model gave the overall best predictions with a fairly low computational cost. The dynamic linear models were less accurate than the dynamic vector auto regressive model in all cases. The VAR model can be used to notify beekeepers of any unusual circumstances in the beehives. If an actual future data value is different than the predicted data value produced by the VAR model, then an abnormality is detected. Schüler [5] explored the correlation between *V. destructor* and *N. ceranae* and colony mortality using different statistical methods. They used a dataset on honey bee colony health containing data on infections and winter losses collected continuously over the span of 15 years. They found that there is a strong relationship between *V. destructor* infection and colony losses. They also found that there is a strong relationship between *N. ceranae* infection and colony losses, but this relationship has low biological relevance since the effects of *N. ceranae* is covered by the effects of *V. destructor* effects on colony health.

[1] https://we4bee.org/

2.1 Algorithmic Works

Braga [6] developed a method for calibrating classification algorithms using internal and external beehive sensors. Three classification algorithms: k-Nearest Neighbors, Random Forest, and Neural Networks. These three algorithms were tested on Western Honeybee beehive datasets monitored over three years. Using these algorithms, Braga introduced a customizable, machine learning based method for predicting honeybee colony health. Murphy [7] developed two novel algorithms using heterogeneous sensor network data from beehives: one for automatic colony status detection and another for local weather prediction. The first algorithm processed multidimensional hive data (oxygen, CO2, pollutants, temperature, and humidity) to determine colony health, while the second exploited correlations between internal hive conditions and external weather patterns to predict rainfall events in the hive's vicinity. Cunha [8] developed a signal processing algorithm using Doppler radar data to assess colony health through forager activity monitoring. The algorithm processes radar return signal strength rather than tracking individual bees, establishing correlations between root mean square (RMS) values and both forager activity ($r^2 = 0.766$) and colony health metrics ($r^2 = 0.731$). This simplified data processing approach provided a non-invasive method for real-time colony health monitoring. Ntawuzumunsi [9] developed mathematical models for energy harvesting in smart beehive monitoring systems. Their algorithms combined three energy sources: piezoelectric transduction from hive weight, bee vibration energy conversion, and electromagnetic harvesting. The key contribution was a resonant frequency optimization algorithm (Equation 16) that accounts for bee wing beat variations (208-277 Hz) to maximize energy harvesting efficiency from colony vibrations, while maintaining health monitoring capabilities. Cecchi [10] developed data processing algorithms for a multiparametric beehive monitoring system. Their key contributions were data validation and filtering algorithms for four sensor types: a weight measurement algorithm using a scale constant k=0.04 for load cell calibration, a sound processing routine for 32kHz MEMS microphone data, a spurious reading detection algorithm for DHT22 temperature/humidity sensors, and a voltage-to-PPM conversion algorithm for CO2 measurements. These algorithms ran on distributed Raspberry Pi nodes in a primary-secondary configuration. Kridi [11] developed pattern recognition algorithms to detect colony absconding risk through thermal analysis. Their algorithms processed temperature data from both inside (microclimate) and outside the hive, using similarity clustering techniques to identify atypical heating patterns that deviate from the optimal 33-36°C range. The approach enabled proactive detection of thermoregulation failure, which is a key indicator of potential colony absconding in semi-arid regions.

2.2 IoT Works

Cota [12] emphasizes the critical role of precision agriculture, particularly in apiculture, through the integration of Internet of Things (IoT) systems for monitoring hive health and mitigating Colony Collapse Disorder (CCD). Cota highlights that temperature, humidity, and other environmental variables are key to understanding hive productivity, and the introduction of low-cost commercial IoT components has contributed to the rise of precision beekeeping systems aimed at improving colony sustainability and management. Rigakis [13] focuses on the decline in bee populations and the need for technology to support beekeepers. His research describes advanced IoT solutions such as gas sensors, vibration sensors, and bee counters. These systems are evolving beyond simple weight or temperature monitoring and are now capable of detecting threats like wasp attacks or infestations, offering a more comprehensive approach to hive health. Tashakkori [14] introduces the Beemon system, a low-cost, Raspberry Pi-based solution for continuous monitoring of beehive conditions, including temperature, humidity, weight, and video/audio recordings. Data is sent via the MQTT protocol to a cloud-based platform for real-time analysis and visualization. The system aims to assist beekeepers in making early interventions and improving hive management with minimal disruption to the bees' natural behavior. Ayden [15] introduces an innovative WSN-based beehive monitoring platform that differentiates itself through the use of a microservices architecture and an open data approach. Ayden emphasizes the importance of sharing IoT data in formats such as RDF/JSON, RDF/XML, and CSV, allowing stakeholders like beekeepers, scientists, and data analysts to access and use the information. The system also focuses on providing scalability and flexibility, essential for managing the increasing number of beehives while supporting technology heterogeneity. Ntawuzumunsi [16] developed a Self-Powered Smart Beehive Monitoring and Control System (SBMaCS), leveraging IoT technology to address the challenge of remote hive monitoring and environmental control. The system integrates multiple sensors, including temperature, humidity, and motion, while utilizing energy harvesting technologies from sources like bees' vibrations to power the devices autonomously. By enabling beekeepers to monitor hive conditions and regulate the environment remotely via a mobile app, SBMaCS not only enhances colony security but also improves honey production. Sánchez [17] developed an electronic system based on the Arduino platform to monitor temperature and humidity in beehives, focusing on thermoregulation in colonies using open-screened bottom boards as a management tool against the Varroa destructor mite. The study found that bee colonies could effectively thermoregulate in hives with open-screened bottom boards, even under winter conditions in a Mediterranean climate, similar to colonies in hives with conventional closed bottom boards. Braga [18] developed a machine learning model to classify honeybee colony health using data from 27 beehives over three years. The study utilized k-Nearest Neighbors, Random Forest, and Neural Networks, integrating internal temperature, beehive weight, weather data, and 703 weekly inspections. The model achieved over 90% accuracy in predicting healthy, unhealthy, and collapsing colonies, with Random Forest reaching 98% accuracy in some scenarios. This research emphasizes the potential for using sensor and inspection data to forecast colony health and enable early detection of issues in apiaries.

2.3 Differentiation from Existing Works

While numerous studies have explored IoT applications in apiculture, our work stands out by focusing exclusively on ruggedized weight sensors to monitor hive health. Unlike systems that rely on a multitude of sensor types—such as temperature, humidity, gas, and vibration sensors—our approach prioritizes weight sensors for several compelling reasons. Weight sensors are renowned for their durability, longevity, non-invasive nature, and relatively low cost, making them ideal for continuous monitoring in challenging outdoor environments.

In contrast to the broader systems developed by researchers like Cota, Rigakis, and Tashakkori, which incorporate diverse sensor arrays and complex data streams, our solution simplifies the monitoring process while still delivering critical insights. By streaming weight data to a cloud server hourly, we ensure real-time analysis with minimal data processing overhead. Our algorithm identifies unhealthy hive conditions and sends timely notifications to beekeepers via an optional connected email system. This streamlined approach not only enhances usability for beekeepers but also reduces costs associated with hardware and maintenance.

Additionally, while existing solutions emphasize multi-sensor integration and advanced predictive models—like Braga's machine learning techniques—our system employs a statistical model rather than a machine learning model due to its lower cost and reduced computational demands. Most existing machine learning models require various sensor inputs and more exhaustive cloud resources, making them less accessible for beekeepers. By leveraging a singular focus on weight monitoring, we create a robust yet cost-effective solution tailored for beekeepers seeking reliable health assessments without the complexity and expense of extensive sensor networks.

In summary, our work distinguishes itself by providing a focused, user-friendly monitoring solution centered on ruggedized weight sensors, optimizing for durability and cost-effectiveness while ensuring timely health assessments of bee colonies.

3 Data Collection

To begin our research, we reached out to around 30 beekeepers and bee farms across Texas, Alabama, and North Carolina, along with research labs at the University of Texas at Austin (UT), Texas A&M University, and Auburn University. We also contacted the United States Department of Agriculture (USDA) for access to relevant datasets. While these sources provided some information on honey production and bee health from beekeeper surveys, the datasets were limited in scope and lacked the specific details we needed, particularly concerning data on collapsed or unhealthy hives.

Many of the institutional datasets we accessed were unsuitable for our study, as they included hives that had been altered for experimental purposes. For instance, some hives were deprived of nutrients or genetically modified, which limited their relevance to our goal of studying natural hive conditions. Given this challenge, we decided to establish our own bee farms to collect primary data under natural conditions.

To address this limitation, we collaborated with bee farm owners for primary data collection. One of our farms, the main one from which we collected data, was located outside Austin TX city limits and off-grid, which posed a unique challenge in monitoring hive health. To overcome this, we developed a solar-powered monitoring system capable of wirelessly collecting and transmitting data from an array of weight and temperature sensors to the cloud. This setup allowed for continuous monitoring and daily reporting on the health of the beehives.

Supplemental Data Acquisition

To complement our primary data, we sourced three supplemental datasets from beekeepers by posting solicitations on online beekeeping forums. These datasets were shared by beekeepers who monitored hive conditions similar to ours, allowing us to expand our data pool while maintaining the integrity of the natural hive environments under study.

[2] One specific request for hive data with specific parameters to complement our dataset.

[2] https://www.facebook.com/TexasApiaryInspection/posts/415433324173702

Fig. 1: The red lines represent the location and division of the hives with respect to the farm. The blue circle represents the wireless solution, the orange circle represents the location of the external sensors, and the dark blue lines represent solar solutions.

4 Experimental Design

Our experimental design consisted of four zones, each containing three hives maintained in healthy conditions throughout the study. Weekly manual inspections were performed to ensure colony well-being, while our sensor array automatically collected data on an hourly basis. The primary metrics monitored included time-series weight data and both internal and external temperature readings. Data collection spanned approximately eight months, providing a comprehensive view of the hives' health.

(a) The image shows a beehive sitting atop a weight sensor used in the collection of our data.

(b) A closer photograph of the sensor sitting underneath a beehive.

Fig. 2: Sensor Location

To ensure the durability and accuracy of our data collection in outdoor environments, we used ruggedized weight sensors designed by sensor manufacturer Solution Bee. While our solution will work with most types of weight scales, these sensors were capable of local data storage and equipped with WiFi connectivity for seamless data transmission to cloud servers. The sensor was configured to poll data on an hourly basis. Additionally, the load cells within these sensors were temperature-balanced to ensure measurement accuracy.

(a) The image shows us installing the sensors on the farm to begin data collection.

(b) The photograph shows us setting up the external sensors, used to collect supplementary data on temperature, humidity, and wind speed.

Fig. 3: Sensor Installation

4.0.1 Importance of Temperature Load Balancing

Temperature load balancing is essential for ensuring accurate weight measurements from sensors exposed to fluctuating outdoor conditions. Without compensation, temperature changes can cause strain gauges in the load cells to experience thermal drift, leading to skewed readings. By employing temperature-balanced load cells, we minimized the impact of these fluctuations, ensuring that weight data accurately reflected hive conditions. In our outdoor settings, where temperatures varied significantly, this calibration was critical to maintaining data integrity. Consistent accuracy was vital to detecting the subtle weight changes that indicate early signs of colony collapse, making temperature load balancing a key component of our predictive system.

5 Data Analysis

The collected time-series data on hive weight and temperature were analyzed to identify patterns and correlations related to hive health and productivity. This comprehensive dataset enabled us to gain insights into the factors influencing bee colony health and honey production, thereby addressing the gaps in existing data sources. We analyzed the data using an algorithm centered around a formula derived using statistical testing.

Our algorithm employs a sliding window approach:
Primary window: 50 consecutive hourly measurements
Secondary window: Subsequent 50 measurements, offset by 25 hours
We compare the two windows to see if the second has a measurably higher standard deviation. Used a cutoff at 2.583 for $p < 0.05$.

The statistical test we used was an F Test, which compares the variances of two samples by giving the ratio between them. This allows us to evaluate if the two samples have similar variances. If the ratio of the two variances is close to one then the two samples are from populations with similar variances. This ratio can be calculated with the following formula:

$$F = \frac{s_1^2}{s_2^2} \tag{1}$$

Where s_1 and s_2 represent the first and second sample respectively.

F tests involve the use of a curve called the F-Distribution to determine if the variances of two samples are from the same population. The F-Distribution is formed by repeatedly taking the ratio of the variances of two samples of data. Once the distribution is formed, two samples can be determined to be from separate populations with different confidence levels based on how far the ratio of their variances is from the center of the distribution. The F-Distribution contains an alpha value which sets the confidence level for which two samples are considered to be from the same population. In the context of beehive weight data, each sample is a window of 50 weight variance data points. So if two subsequent samples are considered to be not from the same population, an abnormality in the beehive is present. We used this F-Distribution for beehive weight variance data to determine a threshold which gives us a high confidence of an abnormality. We implemented this threshold in the main formula of our algorithm to determine whether or not a beehive colony is unhealthy based on the variance of a hive's weight. The formula produces a Hive Index (HI) value which is then used in our algorithm to determine hive health. The formula which produces the HI value is listed below:

$$HI = \eta * \sqrt{\frac{\Sigma_{n=0}^{49}(x_i - \bar{x})^2}{49}} - \sqrt{\frac{\Sigma_{n=25}^{74}(x_i - \bar{x})^2}{49}} \tag{2}$$

In equation 2 the formula we derived uses two windows, each containing a size of 50 beehive weight variance data points with both windows being offset by a size of 25 samples. The formula then computes the standard deviation of the weight variances within each window and compares them to each other by subtracting the standard deviation of the second window from 2.583 (the threshold we determined using the F test which gives us about a 95 percent confidence) times the standard deviation of the first window. If the result or Hive Index (HI) value is greater than 0, that means that the second standard deviation is less than 2.583 times the first one, indicating a hive is healthy. If the result of the calculation is less than 0, that means that the second sample standard deviation is greater than 2.583 times the first one, indicating a hive is unhealthy. The value of 2.583 is the threshold which allows us to accurately determine if the standard deviation of beehive weight variance has changed enough from the first window to the second for the beehive to be considered unhealthy.

(a) Healthy Detection

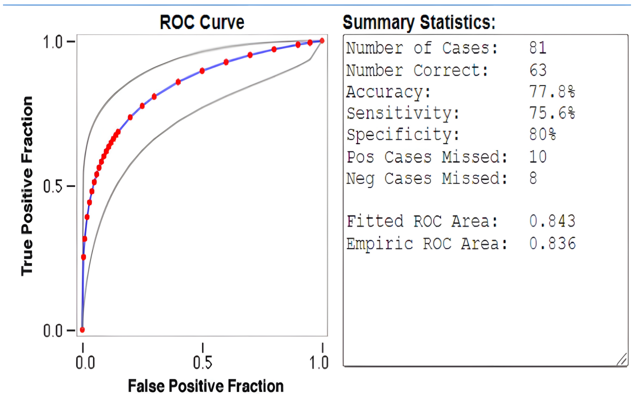
(b) Unhealthy Detection

Fig. 4: Analysis of Results: The graph on the left highlights small variations in kilograms of weight while the graph on the right highlights larger variations in kilograms of weight.

6 Results

We ran our algorithm on multiple datasets, including the ones we collected ourselves and the ones we obtained through outside sources, and saw similar results throughout all the tests. Figures 5a and 5b illustrate one of our results, based on data from the beehives that have already collapsed on the bee farm. In accordance to Figure 5a, our algorithm predicted the hive as being healthy at 201 hours and subsequently unhealthy at 301 hours in accordance with Figure 5b. As seen in Figure 5b, the hive began a full collapse at around 500 hours, meaning our algorithm predicted that the hive was at risk of a collapse around 200 hours before the hive actually collapsed. Had this algorithm been implemented before the hive collapsed, the beekeeper in charge of the farm would have realized the hive was at risk of collapse and intervened to save it. We tested our algorithm on 81 datasets, both self collected and datasets we collected from outside sources. We saw a 77.8% accuracy rate, with an AUC of roughly 0.84. We find that this is a reasonable accuracy for an end-to-end system costing little over $250 for a high end weight sensor.

We have been continuously running this algorithm on our bee farm to further validate its accuracy and reliability. During this time, the algorithm identified several hives as unhealthy. Upon inspection, we discovered that ant infestations were compromising these hives. To address the issue, we removed the ants and elevated the hives on platforms with metal legs, coated with Vaseline to prevent further invasions. After these interventions, the hives recovered, confirming that our early warning system accurately predicted the threat and helped prevent colony collapse.



(a) AUCROC

Testing Dataset

OUTPUT \ TARGET	Positive (1)	Negative (0)	SUM
Positive (1)	31 38.27%	8 9.88%	39 79.49% 20.51%
Negative (0)	10 12.35%	32 39.51%	42 76.19% 23.81%
SUM	41 75.61% 24.39%	40 80.00% 20.00%	63 / 81 77.78% 22.22%

(b) Confusion Matrix

Fig. 5: The figure on the left shows our ROC curve tested on 81 datasets of both healthy and unhealthy hives. We see an accuracy of 77.8% and an AUC of 0.84 which we deem as sufficiently good for the cost of such a system. The figure on the right shows a confusion matrix with our true/false positive and negative rates.

7 Future Work

Looking ahead, we are continuing to refine and expand the scope of this project. We are working closely with sensor manufacturers to integrate the algorithm into commercially available beehive monitoring systems, aiming for a wider rollout. Future versions of the system will incorporate advanced data analytics to increase predictive accuracy and reduce false positives. Additionally, we plan to explore integrating other environmental factors, such as temperature and humidity, to create a more comprehensive monitoring system. By continuously innovating, we are committed to pushing this research forward and ensuring that it delivers maximum impact for beekeepers and the agricultural community at large.

8 Limitations

While our system demonstrated success in predicting Colony Collapse Disorder, several limitations should be noted. The study's primary dataset was restricted to 12 hives in a single geographic location, potentially limiting the model's generalizability across different climatic conditions. The current sensor setup requires consistent cellular connectivity for real-time data transmission, which may not be available in remote apiaries. Additionally, while our algorithm achieved predictive accuracy with simple weight measurements, it does not account for other potential factors in colony collapse such as pesticide exposure or disease presence. Future studies should validate the system across diverse environmental conditions and larger hive populations.

9 Conclusion

We derived a way to predict and prevent honeybee colony collapses using a statistical based algorithm. We incorporated the idea of an F-Test in order to derive the main formula within our algorithm. This algorithm can be used to prevent a few hives from collapsing on an actual bee farm and can be used to prevent more hives from collapse. Currently we are working with the company that makes the weight sensors we used, called Solution Bee, by implementing our algorithm in their weight sensors. Our algorithm is currently being beta tested, but for our next steps we want to see our algorithm being fully implemented on the V6 Version of these Solution Bee Weight Sensors. This research demonstrates the potential of a cost-effective, scalable solution to one of the most pressing issues in modern agriculture: colony collapse disorder. By providing beekeepers with an early warning system that is both accurate and easy to implement, this work contributes not only to the preservation of bee populations but also to the protection of global food security. As we continue to refine and expand this system, our goal is to see it adopted widely by beekeepers, ensuring its impact on agricultural sustainability is felt worldwide.

10 Author Contributions Statement

N.K. and S.K. conceptualized and designed the early warning system for Colony Collapse Disorder. N.K. and S.K. developed the solar-powered monitoring infrastructure and implemented wireless data transmission. N.K. and S.K. set up weight sensors and environmental monitors on the bee farm, collecting hourly data over a year. N.K. and S.K. developed the statistical algorithm using F-test distributions to calculate the Hive Index. N.K. and S.K. validated the model's accuracy, demonstrating successful prediction of hive collapse up to 200 hours in advance. N.K. and S.K. presented findings to beekeeping associations and collaborated with sensor manufacturers for system scalability. N.K. and S.K. successfully intervened in the recovery of 3 out of 12 monitored beehives. Both authors analyzed the results and reviewed the manuscript.

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