BeeUnity: A Predictive Machine Learning System for Improving Hive Occupancy and Beekeeping Outcomes in Makueni County.

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DECLARATION

We, the undersigned group members, hereby declare that the work in this project is original and is the result of our own work, unless otherwise indicated or acknowledged as referenced work. This project has not been submitted to any other academic institution for any degree or qualification.

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APPROVAL

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DEDICATION

This project is dedicated to the hardworking community beekeepers of Makueni County, whose lived experiences, resilience and traditional wisdom inspired the development of BeeUnity. Their commitment to sustainable beekeeping continues to motivate innovations that strengthen local livelihoods and protect our environment.

We also dedicate this work to our families, friends, and mentors, whose continuous support, encouragement, and belief in our abilities made this journey possible. To every person who contributed knowledge, time, or inspiration, this achievement is as much yours as it is ours.

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ABSTRACT

BeeUnity is a predictive analytics system designed to support and enhance community beekeeping practices in Makueni County, Kenya. The project integrates machine learning, environmental monitoring, and community knowledge-sharing to address persistent challenges affecting hive colonization, honey production, and sustainable rural livelihoods. Beekeeping in the region is constrained by unpredictable weather patterns, pest pressures, limited technical expertise, and resource constraints, all of which contribute to low hive occupancy and thus reduced yields.

This study investigates how predictive modeling can be used to empower beekeepers with data-driven insights. The project applies supervised machine learning algorithms to environmental and hive-related data in order to predict hive colonization behavior and identify factors influencing colony success. The system also incorporates a mobile-friendly dashboard to facilitate real-time monitoring, knowledge exchange, and improved decision-making among beekeepers.

The findings of this project are expected to demonstrate that predictive analytics can significantly enhance colony management, increase honey production, and strengthen community collaboration. By combining traditional knowledge with modern technology, BeeUnity aims to contribute to socioeconomic development, environmental sustainability, and digital transformation in rural agricultural communities.

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ACRONYMS AND ABBREVIATIONS

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Many communities in Kenya are known to have practiced traditional beekeeping. Among the Bantu and highland Nilotic communities, honey was a major component in payment of dowry and in marriage negotiations (Affognon et al., 2014). The Ogiek community of Kenya, who are mainly hunters, lived on honey and game meat as their staple food. They used honey to preserve hunted meat. Honey has played, and continues to play, an important role in nutrition and medicine: it is used for treating coughs, wound healing, and as an ingredient in many herbal remedies.

In the tropical parts of Makueni, where Grevillea, Citrus, and acacia trees hum with quiet promise, beekeeping has long been more than a trade. In most semi-arid landscapes of Makueni County, apiculture has long formed an integral part of the cultural and livelihood practices of the Kamba community. The Kamba people have traditionally been associated with beekeeping. Honey was used in important ceremonies such as dowry negotiations and in settling disputes (Kathila, 2017). Other notable uses of honey include making herbal medicines to cure cancerous wounds, colic pains in breastfeeding mothers and their children, hoof and mouth disease in cows among other diseases. Further, bees also play their role in pollination of local crops and fruit trees, thus prompting the need to promote beekeeping.

Beekeeping training emphasizes the need to blend new technology with the old practices to achieve maximum yields. The training covers the use of modern technology and equipment, beehive management, hygienic harvesting techniques, packaging and storage, marketing and book keeping (Affognon et al., 2014). Local study of beekeeping adoption in Makueni is important because it documents adoption barriers but not computerized systems (Kathila, 2017). With no published evidence of deployed computerized hive-monitoring or ML-enabled beekeeping systems specifically in Makuenin, BeeUnity comes in.

1.2 Statement of the Problem

Bee keeping in Makueni is facing increasing strain: pest pressure, weak hive management or delayed hive occupancy, droughts and/or unpredictable weather and resource constraints have been identified as key obstacles (Kathila, 2017). Beekeeping thrives very well in dry climatic conditions and has no direct competition to other farming activities. There is evidence of government initiative to develop beekeeping dating back to the 1950s during the colonial era. Despite these favourable factors, farmer's uptake of beekeeping and production of bee products has been declining in the last ten years (Affognon et al., 2014). Training is required to monitor colony health, hive colonization trends, forecast swarming behavior, or determine the best environmental conditions for bee activity. Through proper training educated youth and other farmers would acquire skills, develop interest and change their perception on the viability of beekeeping as an economic activity. Training further brings about standardization and output of hygienic products acceptable to all markets (Kathila, 2017). This is a serious problem because bees play a crucial role in pollination of local crops and fruit trees production and therefore the need to promote bee keeping. For example, a study by Kathila (2017) found out that 73% of farmers in Makueni County considered beekeeping as a viable economic activity while only 30% practiced beekeeping.

If the problem is not solved, Makueni's beekeepers will continue to face poor harvest returns, reduced pollination rates, and a weakened ecosystem balance. Further, the younger generation may also lose interest in beekeeping, threatening the sustainability of the industry.

1.3 Objectives

1.3.1 General Objective

The general objective is to develop a predictive ML system for boosting hive occupancy.

1.3.2 Specific Objectives

1. To analyze beekeeping practices by farmers in Makueni County
2. To develop predictive analytics with a machine learning approach for community beekeeping in Makueni County.
3. To evaluate the performance of the predictive Machine Learning algorithm.

1.4 Research Questions

1. How can machine learning models improve hive colonization and colony monitoring?
2. What environmental factors most affect colony success in Makueni?
3. How can digital tools foster unity and knowledge sharing among beekeepers?

1.5 Significance of the Study

The significance of this study is that it introduces a data-driven, predictive approach to addressing the longstanding challenges faced by community beekeepers in Makueni County. Although beekeeping is a culturally-tied, routed, and livelihood-supporting activity among the Kamba community, hive occupancy rates remain low due to pests, inconsistent environmental conditions, limited training, and the absence of modern monitoring techniques. By developing a predictive machine learning system, this project offers a practical technological solution that can directly improve hive management and decision-making in the apiculture industry.

The importance of this study to community beekeepers is that it provides early insights on colony behaviour, forecasts hive colonization likelihood, and highlights environmental conditions that directly influences colony success. With such information at hand, beekeepers can make timely and informed decisions that reduce losses, improve harvesting schedules, and enhance overall productivity. The findings are also valuable to agricultural extension officers, cooperatives, and county-level development programs, as the predictive insights can guide training programs, resource allocation, and strategic planning. The system demonstrates how digital tools can complement existing indigenous knowledge, thereby modernizing traditional apiculture practices without the need of replacing their own cultural techniques.

Regarding policy makers and development agencies, the project contributes evidence that machine learning and environmental data integration can strengthen rural livelihoods. This contribution aligns well with the national goals on agricultural digitization, food security, and sustainable rural development. The model provides a pathway for scalable digital transformation in apiculture and other smallholder farming activities, especially in the Makueni region. Furthermore, the study is significant to the data science and environmental informatics academic community as it applies supervised machine learning to a real-world agricultural sustainability problem. The project contributes to research on using predictive analytics in low-resource rural settings and forms a basis for future system enhancement, such as realtime sensor integration for bioacoustic hive activity monitoring.

The project further holds social significance by promoting community collaboration and knowledge-sharing. Through the project's digital platform, beekeepers can exchange experiences, strengthen cooperative networking and build collective resilience. Improved hive occupance and honey yields directly translate into household incomes, enhanced pollination, and stronger ecosystem balance in Makueni County.

1.6 Scope of the Study

This study focuses on the development and evaluation of a predictive machine learning system designed to improve hive occupancy and beekeeping outcomes in Makueni County. The scope of this project is limited to community-based beekeeping practices within the county's semi-arid regions, where environmental variability, pest pressure, and low hive colonization rates have been identified as major challenges.This study examines historical weather patterns, environmental variables, and hive-related factors sourced from publicly available datasets and community-provided information. These variables form the basis for training and testing supervised machine learning models aimed at predicting hive colonization likelihood and identifying factors that influence colony success. The prototype developed under this study includes a machine-learning prediction engine and a user-friendly dashboard for visualizing insights. It is important to note however that this project does not extend to the deployment of physical IoT sensors or automated hive-monitoring hardware. Instead, the system offers software-based predictive analytics and digital knowledge-sharing components.

Geographically, the study is confined to selected community beekeeper groups in Makueni County. While the modelling approach may be adaptable to a wide range of other regions, validation and testing are restricted to the environmental conditions and practices that are characteristic to Makueni County. The study further limits itself to three core dimensions: analyzing local beekeeping practices, building predictive analytics using machine learning, and evaluating the performance of the developed model. Broader economic, market-based, or national-policy analyses fall outside the scope except where they directly support the ultimate interpretation of the project results. Conclusively, the study remains centred on demonstrating how predictive analytics can strengthen hive management, enhance decision-making, and support community beekeeping in Makuenin County.

1.7 Limitations of the Study

This study acknowledges a number of limitations that may influence the interpretation and generalization of its findings. Firstly , the predictive models rely on secondary environmental datasets that, while reliable, may not fully reflect the hyper-local microclimatic variations experienced within Makueni County. The absence of on-site IoT sensors or continuous hive-level monitoring means that the model predictions are based on aggregated or interpolated data rather than real-time, hive-specific measurements. Secondly, the study is limited in itself by the availability and quality of community-provided beekeeping data. SOme beekeepers may lack consistent record-keeping, leading to gaps or inconsistencies in hive occupancy, harvesting patterns, or pest incidence data used for model training. These are some of the constraints that may affect the precision of the machine learning outputs.

Thirdly, this project solely focuses on software-based predictive analytics and does not evaluate the impact of the model in live field deployment. Factors such as user adoption, behavioural changes witnessed in beekeepers, and the long-term effects of predictive insights on productivity are beyond the scope of this study. Moreover, the geographic scope is restricted to Makueni County, and while the modelling approach is adaptable, environmental conditions, floral calendars, and beekeeping practices vary across the country. This limits the external validity of the findings when applied to different ecological zones unless further calibration is performed on the underlying model.

It is important to note as well that the study evaluated only a selected set of supervised machine learning algorithms, and that other potentially useful approaches such as reinforcement learning or hybrid sensor-based models, were not explored in their entirety - although their contributions towards the system would be an improvement - due to scope and time constraints.

Finally, resource limitations, including computational capacity and field access, restricted the depth of data exploration and the scale of community engagement. Broader longitudinal studies would offer stronger evidence of long-term benefits. While these limitations constrain certain aspects of the study, they however do not diminish its contribution. Instead, they highlight areas for future research, system refinement, and field deployment.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews existing literature related to beekeeping practices, hive occupancy challenges, environmental factors affecting hive colonization, and the application of predictive analytics and machine learning in agriculture. The review establishes the theoretical and empirical foundations upon which the BeeUnity system is built, highlighting the relevance of digital technologies in modern apiculture and identifying gaps that the current study seeks to fill.

2.2 Traditional and Modern Beekeeping Practices

2.2.1 Traditional Beekeeping Practices in Kenya

Traditionally, beekeeping has been a vital livelihood activity in many African communities, particularly in Kenya, where traditional apiculture is characterized by the use of log hives, minimal intervention, and reliance on indigenous knowledge. Among communities such as the Kamba and Ogiek, honey serves not only as a source of nutrition but also holds significant cultural and medicinal value, reflecting the deep-rooted importance of bees in rural life. Traditional practices have persisted for decades, showcasing a rich heritage of beekeeping that is closely tied to local customs and ecological conditions. However, traditional beekeeping methods face several challenges. These challenges include low hive occupancy rates, vulnerability to pests, and reduced honey yields, which can hinder the economic viability of beekeeping as a livelihood. The reliance on indigenous knowledge, while valuable, may not always address the modern challenges faced by beekeepers, leading to calls for a more integrated approach that combines traditional practices with contemporary techniques.

2.2.2 Modern Beekeeping Practices

On the other hand, modern beekeeping introduces a range of improved practices aimed at enhancing productivity and sustainability. This includes the use of advanced hive designs, colony management techniques, hygienic harvesting methods, and structured training programs for beekeepers[2]. The introduction of movable frame hives, for instance, allows beekeepers to manage colones more effectively and harvest honey without damaging the combs, which is a significant improvement over traditional methods. Studies, such as those done by Affognon et al. (2014), emphasize the importance of blending traditional knowledge with modern tools to maximize productivity while maintaining cultural relevance [1]. This hybrid approach aims to address the limitations of traditional practices while respecting the cultural significance of beekeeping in local communities.

2.2.3 Challenges in Adoption of Modern Practices

Even though modern beekeeping technologies serve several advantages, regions like Makueni County in Kenya still experience low adoption rates of these innovations. This indicates a gap between the availability of modern techniques and their practical application in local contexts. Factors contributing to this low adoption may include a lack of access to training, financial constraints, and the need for innovations that are both accessible and adaptable to local conditions. Moreover, the transition from traditional to modern practices requires careful consideration of local customs and ecological factors. Beekeepers must be equipped with the necessary knowledge and skills to implement modern techniques effectively, which underscores the importance of training and capacity-building initiatives.

2.3 Hive Occupancy Challenges in Semi-Arid Regions

Hive colonization is influenced by multiple environmental, biological, and human factors. Semiarid regions like Makueni face unpredictable weather patterns, frequent droughts, and limited forage availability. Kathila, (2017), notes that pest pressure, poorly timed harvesting, and inconsistent hive management significantly hinder hive occupancy. Declining honey production in the region contrasts with the high potential of beekeeping as an economic activity, with studies consistently highlighting the need for improved monitoring, better forecasting of hive colonization periods, and enhanced decision-making support for farmers. These gaps are the underlying factors prompting the adoption and relevance of predictive analytics in supporting hive management.

2.4 Environmental Factors Affecting Colony Success

Colony success is closely attributed to environmental conditions such as temperature, humidity, precipitation, nectar flow, and vegetation cover. Research in climate-sensitive agriculture unveils an interesting fact that bees respond sharply to microclimatic changes that affect foraging behaviour, swarming, and nest selection. Weather datasets such as ERA5, CERRA, and Open-Meteo have increasingly been used in agricultural modelling to understand ecosystem dynamics. By integrating such meteorological data with local hive information, predictive systems can identify patterns and offer anticipatory insights into colony behavior. These findings strongly back the usage of environmental data as a key input in the BeeUnity predictive model.

2.5 Predictive Analytics in Agriculture

The use of predictive analytics in modern Agriculture has gained prominence for forecasting crop yields, estimating soil moisture, monitoring disease outbreaks, and supporting resource allocation. Machine learning models have been applied successfully in livestock monitoring, crop health detection, irrigation optimization, and environmental forecasting. The core value of predictive analytics lies in its ability to uncover hidden relationships in data and produce actionable insights that in turn improve decision-making. In rural and resource-constrained settings, such tools can significantly enhance planning efficiency and reduce losses. However, literature shows that there is a limited application of machine learning in apiculture, particularly in East Africa contexts. This presents an opportunity for innovation in beekeeping technology.

2.6 Machine Learning Applications in Apiculture

In this era of Artificial Intelligence (AI) and Internet of Things (IoT), emergent research explores the use of smart sensors, computer vision, sound analysis, and ML models to track colony activity, detect swarming, and predict hive health. There have been a number of applied solutions in the same, for example, there have been computer vision models for detecting bee flight patterns and hive entry rates. Acoustic monitoring to classify hive states using frequency signatures, environmental modelling linking temperature and humidity to colony development, and predictive models for hive occupancy and honey yield estimation. Even with these advances, such technologies remain largely experimental and are rarely fully deployed in rural African contexts due to cost, infrastructural limitations, and the lack of digital literacy amongst the beekeepers. BeeUnity fills this gap by designing a low-cost, data-driven system that uses accessible weather datasets and community knowledge rather than expensive hardware.

2.7 Digital Tools and Knowledge Sharing in Community Agriculture

Research on rural development emphasizes the importance of digital platforms that facilitate knowledge exchange, cooperative learning, and timely dissemination of agriculture advisories. Mobile dashboards, SMS alerts, and web portals have been used to enhance communication between farmers, agricultural extension officers, and cooperatives. Digital tools play significant roles in increasing farmer's access to technical information, improving coordination among community groups, promoting standardized practices, and enabling collective problem-solving. For beekeeping communities, such platforms can help in bridging knowledge gaps, strengthening collaboration and promoting best practices that work towards enhancing hive occupancy and productivity.

2.8 Identified Research Gaps

Through the reviewed literature, there have been several emerging gaps:

1. Limited use of predictive analytics in Kenyan apiculture, especially in semi-arid counties like Makueni.
2. Scarcity of hive-level digital monitoring solutions tailored to low-resource, community-based beekeeping.
3. Insufficient integration of environmental data with beekeeping decision-making tools.
4. Minimal empirical research on how machine learning can forecast hive colonization likelihood.
5. Lack of community-centered digital platforms that merge predictive insights with knowledge sharing.

The identified gaps justify the development of BeeUNity and guide the direction of the current study.

CHAPTER THREE - RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the research design, data sources, data collection methods, system architecture, machine learning techniques, and evaluating procedures used in the development of the BeeUnity predictive analytics system. The methodology is structured to address the study objectives by applying data science techniques to real-world beekeeping challenges in Makueni County.

3.2 Research Design

The study adopted a quantitative, applied research design combined with a system development approach. Quantitative methods were used to analyze environmental and hive-related data, while system development methods guided the design and implementation of the predictive machine learning system. The research followed an iterative workflow consisting of data collection, preprocessing, model development, evaluation, and system integration. This design was selected because it enables the practical application of machine learning to solve a clearly defined agriculture problem.

3.3 Study Area

th e study was conducted in MakueninCounty, semi-arid region in southeastern Kenya. The county is well known for community-based beekeeping, particularly among the Kamba community. Makueni's climatic conditions, characterized by variable rainfall, periodic droughts, and temperature fluctuations, make it an ideal case study for examining the environmental influences on hive occupancy and colony success.

3.4 Data Sources and Data Collection

The study utilized secondary data sources combined with contextual information from community beekeepers.

3.4.1 Environmental Data

Environmental data were obtained from reputable open-access meteorological datasets, including:

- Temperature
- Rainfall
- Humidity
- Wind patterns, and
- Seasonal climatic indicators

These datasets provide historical and near-real-time weather information relevant to beekeeping activity and colony behaviour.

3.4.2 Beekeeping and Hive Data

Beekeeping-related data included:

- Hive occupancy statues
- Hive type and placement information
- Seasonal harvesting records
- Pest occurrence indicators

Due to limited digital record-keeping among the community beekeepers, some hive-related data were generalized or inferred based on available reports and documented practices.

3.5 Data Preprocessing

Prior to model development, the collected data underwent several preprocessing steps to ensure quality and suitability for machine learning analysis. These steps included:

- Handling missing values through imputation techniques
- Normalization and scaling of numerical variables
- Encoding categorical variables
- Feature selection to identify variables most relevant to hive occupancy

Data preprocessing was essential for improving model accuracy and reducing noise.

3.6 System Architecture

The BeeUnity system was designed as a modular predictive analytics platform consisting of the following components:

1. Data Layer - responsible for storing environmental and hive-related datasets.
2. Processing Layer - performs data cleaning, feature engineering, and model execution.
3. Machine Learning Layer - hosts the predictive models
4. Application Layer - provides a user-facing dashboard for visualization and interpretation of results.

This architecture supports scalability and future integration with real-time data sources.

3.7 Machine Learning Model Development

The study employed supervised machine learning techniques to predict hive occupancy likelihood. The target variable was hive occupancy status, while input features included environmental and contextual variables. The selected algorithms included:

- Logistic Regression
- Decision Trees
- Random Forest

These algorithms were chosen due to their interpretability, suitability for classification tasks, and effectiveness with structured data. Model training was performed using a split dataset, with separate training and testing subsets.

3.8 Model Evaluation

Model performance was evaluated using standard classification metrics, including:

- Accuracy
- Precision
- Recall
- F1-score

These evaluation metrics provided a comprehensive assessment of model reliability and predictive capability. Comparative analysis was conducted to identify the best-performing model for the BeeUnity system.

3.9 System Implementation and Visualization

A prototype dashboard was developed to present the predictive insights in a user-friendly format. The dashboard enables users to:

- View predicted hive occupancy trends
- Explore environmental factor impacts
- Support decision-making for hive placement and management

The interface was designed with accessibility in mind to support use by community beekeepers and extension officers.

3.10 Ethical Considerations

The study adhered to ethical research principles. No personally identifiable information (PII) was collected from individual beekeepers. All datasets used were publicly available or anonymized. The system was designed to support, not replace, traditional beekeeping knowledge and practices.

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