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Smart Cattle Health Monitoring and Farming Productivity Management Using IOT and CNN

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Abstract: The agricultural industry plays a pivotal role in supporting global food security and sustaining economies. Within this industry, cattle farming represent a significant sector, providing essential resources like meat, milk, and other dairy products. However, traditional cattle farming practices often face challenges related to monitoring, managing, and predicting various aspects of cattle health and productivity. In recent years, the advent of technology has opened up new possibilities for transforming traditional farming practices into more efficient, data-driven systems. The integration of smart devices, IoT sensors, machine learning algorithms, and real-time data analytics has paved the way for innovative solutions that can address the limitations of conventional cattle farming. The integrated embedded system proposed in this paper aims to revolutionize cattle farming practices by providing a comprehensive solution to enhance cattle well-being and optimize farming efficiency. It encompasses four crucial areas: real-time monitoring and health management, milk production prediction, artificial insemination scheduling, and disease analysis with first aid recommendations. By utilizing cutting-edge IoT, sensors, machine learning algorithms, and image recognition techniques the system enables farmers to monitor cattle health in real-time, predict milk production accurately, schedule artificial insemination effectively, and promptly identify and manage cattle skin diseases. Overall, the system has archived 91% high accuracy through these advancements, also empowers farmers to make data-driven decisions, ensuring proactive measures to prevent health issues, enhance productivity, and fosters a sustainable and profitable agriculture industry.

Keywords: Cattle, Algorithms, IoT, Machine learning, Artificial intelligence, Smart cattle, IoT, CNN, Farmimg, Milk production, Health montioring.

I. INTRODUCTION

One of the central issues we are addressing is the need for real-time monitoring and health management of cattle. Detecting health anomalies promptly is crucial for maintaining the overall well-being of livestock and maximizing productivity. Additionally, predicting milk production accurately based on various factors is a pressing concern for resource optimization and better farm management. Furthermore, our research delves into enhancing cattle breeding practices through AI-driven scheduling of artificial insemination, which has far-reaching implications for the long-term sustainability of cattle herds.

By addressing these issues, our project aims to provide practical and innovative solutions that empower cattle farmers in the Northern region. Through a holistic approach that integrates cutting-edge technologies and data-driven insights, we strive to enhance cattle farming practices, improve productivity, and contribute to the well-being of both farmers and their livestock. This endeavor reflects our commitment to making a positive impact on the agricultural landscape by alleviating the challenges faced by cattle farmers and fostering sustainable development in the region.

The integration of cutting-edge IoT sensors in the proposed system for real-time monitoring and health management is a transformative advancement for modern cattle farming practices. By providing farmers with access to real-time data and instant alerts, the system enables them to closely monitor crucial parameters related to cattle health, behavior, and environmental conditions. With timely insights into their livestock's well-being, farmers can swiftly identify signs of distress or illness, allowing for immediate and proactive measures to prevent disease spread and administer timely medical interventions. Accurate milk production prediction is a pivotal aspect of modern cattle farming practices, enabling farmers to optimize resource

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management and enhance overall productivity. using advanced machine learning algorithms, the proposed integrated embedded system analyzes various influential factors, such as climate conditions, age of the cattle, staffing period, and potentially other relevant variables. By forecasting milk production levels, farmers can make data-driven decisions regarding feed distribution, efficiently schedule milking activities, and ultimately improve milk output.

Optimizing breeding practices is a critical component of successful cattle farming, and artificial insemination plays a significant role in this process. The proposed system introduces a revolutionary approach to artificial insemination scheduling, utilizing advanced technologies to enhance breeding outcomes. By considering multiple factors, including cows' breed, age, health index, weight index, and environmental history, such as temperature and humidity, the system can accurately Predicting next Suitable AI date

The health and well-being of cattle are crucial for sustainable and profitable farming practices, as diseases can have detrimental effects on livestock productivity and economic outcomes. In response to these challenges, the proposed integrated embedded system introduces a groundbreaking solution for disease analysis and first aid recommendations. Leveraging advanced image recognition techniques, specifically Convolutional Neural Networks (CNN), the system can accurately identify visual symptoms associated with cattle skin diseases, such as Lumpy Skin Disease, Photosensitization, Warts, and Fly irritation. By promptly detecting and diagnosing these ailments, the system empowers farmers to take timely and appropriate first aid measures, effectively managing disease outbreaks and minimizing economic losses. This innovative approach represents a significant advancement in cattle healthcare, providing farmers with valuable tools to enhance disease management and ensure the overall health and productivity of their livestock.

II. LITTERATURE SURVEY

This section conducts a comprehensive literature review focusing on the themes central to our research on enhancing cattle welfare through IoT-enabled surveillance, health monitoring, and stress prediction. The review delves into relevant studies and findings concerning the implementation of IoT technologies for cattle welfare improvement, including aspects such as surveillance, real-time health monitoring, and stress prediction in livestock. Through this analysis, Research aims to gain insights into the current state of research in this field and identify potential approaches to optimize cattle well-being and management using advanced IoT-based systems.

Researches introduce [1,2], introduces a framework and prototype for a crop monitoring and response system tailored to meet the specific needs of farmers. On the other hand, the primary contribution of M. S. Farooq introduces [2] lies in providing a comprehensive categorization of security threats specifically relevant to Smart Farming (SF) and Precision Agriculture (PA) domains. Moreover, the study presents a taxonomy that aids in detecting and analyzing APT (Advanced Persistent Threat) attacks and other security threats in SF and PA environments.

A systematic search of peer-reviewed articles was performed [3], focusing on studies that specifically addressed cows' health, production, and behavior/management in AMS settings. Modeling approaches, particularly Machine Learning, play a central role in optimizing dairy cow management within Automated Milking Systems. While health detection, especially for mastitis, is the dominant research focus, there is a need for more studies on milk production prediction and cows' behavior/management. Machine Learning (ML) emerged as the most widely used modeling method, featuring in 63% of the reviewed studies. Statistical analysis accounted for 14%, fuzzy algorithms for 9%, deterministic models for 7%, and detection algorithms for 7% of the studies. Notably, a significant majority of the reviewed articles (82%) primarily focused on the detection of cows' health, with particular attention to mastitis, while only 11% evaluated milk production.

K. Maatje and R. Amann [4,5], aims to explore the current state of research in AI scheduling to optimize breeding practices. By considering various factors such as cows' breed, age, health index, weight index, and environmental history (temperature and humidity), smart scheduling techniques can predict the most suitable time for insemination. By considering the cows' breed and health parameters, the researchers achieved improved timing accuracy, resulting in higher pregnancy rates and healthier offspring.

K. Maatje, L.D. Rowe [6,7] introduce a CNN-based approach for the classification of Lumpy Skin Disease (LSD) in cattle. The researchers trained the model using a large dataset of images showing visual symptoms of LSD. The results demonstrate high accuracy in disease identification, enabling timely intervention and first aid recommendations for affected

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animals. Also proposes an automatic detection and recognition system for Photosensitization in cattle based on CNN.

III. METHODOLOGY USED IN PROPSED TECHNIQUE

Figure 1 depicts the comprehensive system diagram of this integrated solution for enhancing cattle welfare through IoT-enabled real-time monitoring, health management, milk production prediction, disease analysis, and first aid recommendations. Building on insights from the literature review this paper has designed and developed a prototype that combines cutting-edge technologies to revolutionize cattle farming practices.

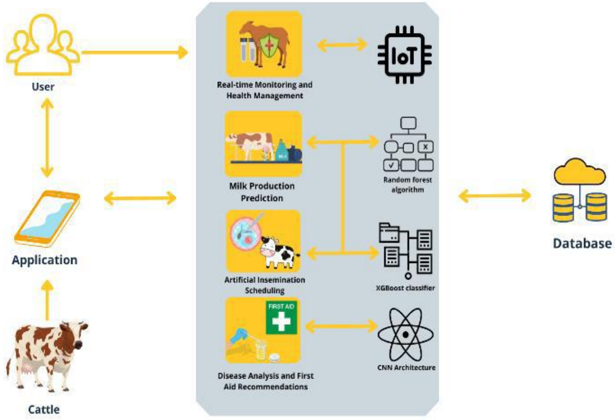

Figure 1: System diagram

A) Real-time Monitoring and Health Management

This innovative device incorporates five sensors to enhance cattle monitoring and well-being. The first sensor utilizes GPS technology to track the location of cows, ensuring efficient management and security. Additionally, four other sensors measure critical health parameters: body temperature, heart rate, acceleration, and humidity. The real-time data collected from these sensors is seamlessly transmitted to Google Firebase for immediate storage and accessibility. Through our user-friendly interface, farmers can visualize real-time data on cow location, body temperature, heart rate, acceleration, and humidity. Furthermore, the system incorporates an advanced stress prediction model. By enhancing machine learning techniques, this model assesses changes in cow behavior, walking patterns, body temperature, and heart rate. These indicators often fluctuate when a cow is under stress. The system architecture Fig 2 ensures timely data transmission, enabling farmers to monitor and assess the well-being of cattle based on real-time readings. This integration of technology aims to revolutionize cattle farming practices by providing actionable insights that contribute to improved cattle welfare and more efficient management.

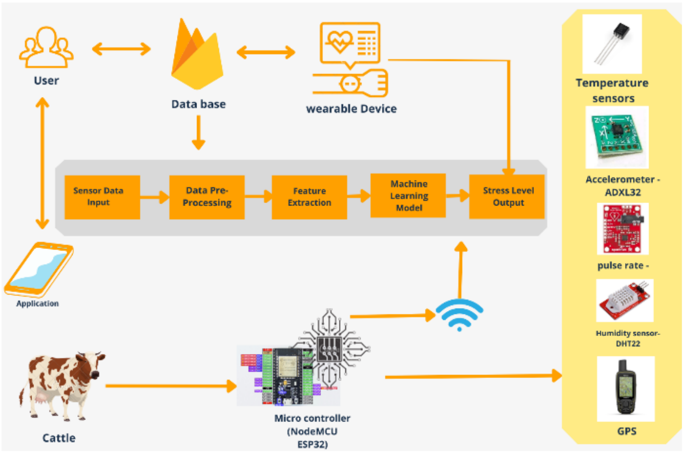

Figure 2: Timely data transmission of Real-time Monitoring Diagram

Although the system initially lacked a comprehensive dataset, data was gathered from both healthy cows with normal readings and stressed cows displaying irregular patterns. By comparing these datasets, distinct markers of stress were successfully identified, paving the way for the development of a robust stress prediction model.

In subsequent stages, the system's capabilities will be further enhanced. An extensive dataset encompassing a diverse range of cow behaviors and stress levels is actively being created. This dataset is utilized to train and refine the stress prediction model, enabling more accurate and reliable stress assessments. By harnessing the power of data-driven insights, the system aims to empower farmers with real-time stress detection, contributing to improved cattle welfare and ultimately transforming the landscape of modern cattle farming practices.

These input sensors are integrated with the NodeMCU, a versatile IoT development board, which processes the sensor data and establishes a connection to the Firebase cloud database. Through this connection, the real-time readings from each sensor are stored securely and made accessible to users through the Firebase platform. The system capitalizes on the NodeMCU ESP32 development board, harmoniously integrating an array of sophisticated sensors to elevate cattle monitoring and well-being. These sensors include the ADXL32 accelerometer, instrumental for capturing acceleration and gauging cow behavior shifts; the AD8232 ECG(Electrocardiogram) module, adept at discerning

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pulse rates and illuminating cardiovascular health dynamics; the NEO-6M GPS(Global Positioning System) module, proficiently tracing cattle locations to streamline management and fortify security; and the DHT22 humidity sensor, dutifully evaluating environmental moisture levels for insights into cattle health and responses.

B) The Milk Production Prediction

In this endeavor, a predictive framework has been adeptly employed to anticipate milk production which depict in Fig 3, drawing insights from four influential factors: climate, age, staffing period, and cow health. The data collection process was meticulously executed through a manual approach, involving the systematic acquisition of data from three distinct farms located in the Jaffna region. Harnessing the efficacy of the Random Forest algorithm, this system has ingeniously crafted a predictive model that deftly extrapolates and forecasts milk production.

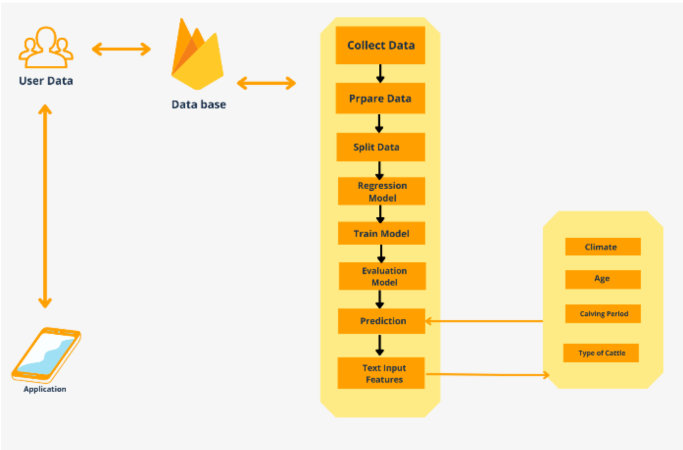

Figure 3: Anticipate milk production Diagram

The interplay of these four factors holds paramount significance within the predictive model. The climate factor encapsulates the environmental conditions that invariably impact milk production. The age of the cows, as well as the prevailing staffing period, also emerges as crucial contributors. Notably, the health status of the cows intertwines with these factors, serving as a key determinant in predicting milk production outcomes. By seamlessly weaving together the data collected from these farms, the Random Forest algorithm orchestrates an intricate dance of variables, culminating in a robust predictive framework.

a) Random Forest

The methodology for predicting milk production employing the Random Forest algorithm, centered on the four factors of climate, age, staffing period, and cow health, is outlined as follows. Data collection encompasses manual compilation from three Jaffna farms, amassing details on climate conditions, cow age, staffing periods, and cow health status, while juxtaposing them with milk production records to forge a comprehensive dataset.

Subsequent data preprocessing involves meticulous cleansing and organization, resolving absent values and anomalies, with the integration of categorical variables into numerical formats. The dataset is bifurcated into training and testing subsets, facilitating model evaluation. Feature selection evaluates the significance of each attribute in prediction, unraveling pivotal factors that contribute significantly to model efficacy.

The core of the process resides in model development, where the Random Forest algorithm is enlisted, an adept ensemble learner suited for regression tasks. This algorithm is harnessed to train the model using the chosen attributes, capitalizing on its adeptness in untangling intricate interplays among variables. Moreover, Fig 4 shows Model evaluation rigorously tests performance via relevant regression metrics, gauging accuracy and reliability. Fine-tuning parameters optimizes the model, ensuring superior results when applied to unseen data.

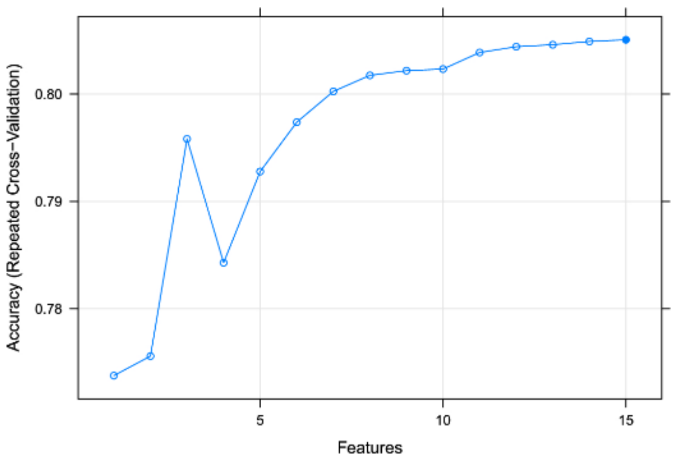

Figure 4: Model evaluation rigorously tests performance

Correlation analysis has yielded significant insights into the interplay between various factors and milk production. Younger cows exhibit a negative correlation, indicating higher milk production, highlighting age's impact. The minor negative correlation between climate and milk production suggests

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climate's limited influence. Milk production diminishes with months after calving, denoting temporal dynamics. Notably, Jersey cows display notable positive correlation, while the local breed exhibits a substantial negative correlation, underscoring breed-related disparities. The proficient Random Forest Regressor model, boasting a mean squared error of approximately 0.89, solidifies its predictive prowess, enhancing estimations of milk production based on the given factors. Together, these correlations and model evaluations holistically enhance comprehension of intricate dynamics governing milk production, empowering data-driven insights to inform judicious choices in cattle farming practices.

b) Artificial Insemination Scheduling

The facet of Artificial Insemination Scheduling constitutes a pivotal element of the system Illustrated in Fig 5, spotlighting the enhancement of breeding practices via intelligent artificial insemination timing. Through a nuanced amalgamation of factors encompassing cow breed, age, health index, weight index, and historical environmental conditions (temperature and humidity), the system adeptly forecasts the optimal date for the subsequent insemination event. This predictive precision engenders a lineage of robust, genetically superior offspring, significantly bolstering the long-term sustainability and genetic vitality of the cattle herd. The predictive prowess of this component is underpinned by a multifaceted algorithmic approach, leveraging the capabilities of three distinct algorithms: XGBoost classifier, Random Forest, and Support Vector Machine (SVM). This convergence of algorithms empowers the system to discern intricate patterns within the data and make accurate predictions regarding the opportune time for artificial insemination.

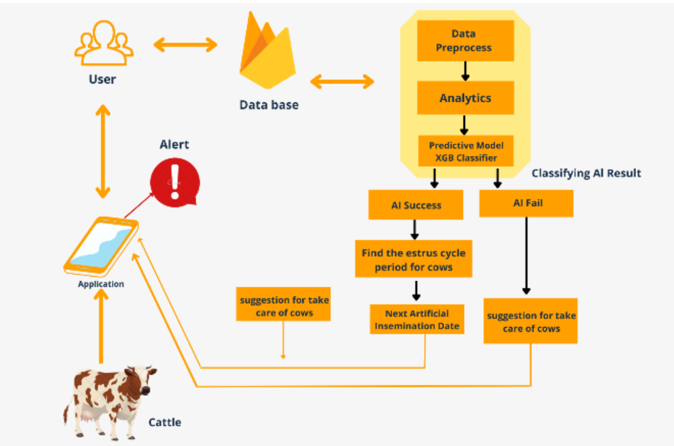

Figure 5: Artificial Insemination Scheduling system

Data acquisition further bolsters the system's efficacy. Information is culled from varied sources, including the veterinary hospital and Jaffna farms, reflecting both clinical expertise and real-world farm conditions. This manual data collection ensures a comprehensive dataset that encapsulates diverse scenarios and conditions, further enhancing the algorithmic predictions.

c) XGBoost classifier, Random Forest, and Support Vector Machine (SVM)

XGBoost stands for eXtreme Gradient Boosting, and it excels at handling complex relationships within data. In the context of Artificial Insemination Scheduling, the XGBoost classifier learns to differentiate between optimal and suboptimal insemination dates based on various input factors such as cow breed, age, health index, weight index, and environmental history. It does this by iteratively building an ensemble of weak learners (decision trees) and optimizing their weights to minimize prediction errors. During training, the XGBoost algorithm progressively refines its understanding of the data, focusing on instances where it initially struggled to make accurate predictions.

In the artificial insemination, Random Forest analyzes the provided factors to discern patterns that indicate the optimal timing for insemination. The randomness in tree construction and the subsequent aggregation help mitigate overfitting and enhance the algorithm's generalization to new data. Moreover, SVM seeks to delineate the decision boundary that distinguishes favorable from unfavorable insemination dates based on the input factors. It does so by maximizing the margin between the support vectors of different classes, ensuring robust separation.

From the three algorithms, the XGBoost classifier emerged as the most fitting for the data at hand. It achieved impressive accuracy scores of 90% and 81% on the training and test datasets, respectively. The balanced F1 scores for both classes signify that the trained model is not biased towards any particular outcome, reinforcing its fairness and robustness. These outcomes collectively affirm the efficacy of the XGBoost classifier in capturing the complexities of artificial insemination scheduling and showcasing its potential for accurate predictions in real-world cattle farming scenarios.

C) Disease Analysis and First Aid Recommendations

The Disease Analysis and First Aid Recommendations which shows in Fig 7 addresses the critical issue of cattle health

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by harnessing advanced image recognition techniques. Specifically, Convolutional Neural Networks (CNN) are employed to analyze visual symptoms associated with prevalent cattle diseases, including Lumpy Skin Disease, Photosensitization, Warts, and Fly irritation. These diseases have the potential to significantly compromise cattle well-being and productivity, translating to substantial economic losses for farmers.

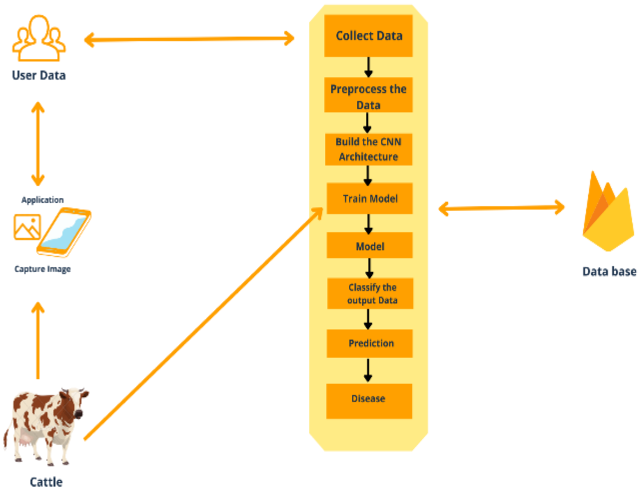

Figure 6: Disease Analysis and First Aid Recommendations

This classification process is built upon the principles of Supervised Learning, employing classification algorithms to categorize images into specific disease classes. To facilitate this, a robust dataset of 130 training images has been curated from Kaggle, representing the five distinct disease classes.

Two distinct models, Inception ResNet v2 and Efficientnet-B1, have been selected for building the disease classification model. These models leverage their unique architectures and feature extraction capabilities to identify subtle visual patterns associated with each disease. By training these models on the curated dataset, the system enables accurate disease diagnosis and provides prompt first aid recommendations to farmers, enabling them to respond effectively to disease outbreaks and mitigate their impact.

Through this advanced image analysis approach, the system empowers farmers with actionable insights and recommendations, ensuring timely and efficient management of cattle diseases. The comparative utilization of Inception ResNet v2 and Efficientnet-B1 underscores the system's commitment to leveraging cutting-edge technology for accurate disease identification and aiding farmers in safeguarding cattle health and productivity.

D) CNN Architecture

It begins with the input layer, where preprocessed images are resized for consistency. Convolutional and max-pooling layers then extract intricate features like edges and textures, preserving essential information. Additional pairs of these layers progressively abstract higher-level features. The flattened feature maps are channeled into fully connected (dense) layers, which decipher complex patterns. The output layer, utilizing softmax activation, generates class probabilities corresponding to disease classes. After compilation and training, the model's performance is assessed and fine-tuned. Upon inference, it predicts disease probabilities, allowing post-processing to map to specific classes and generate relevant first aid recommendations.

By harnessing the power of pre-trained models, specifically those pretrained on 'imagenet,' the system capitalizes on the wealth of knowledge these models have accumulated from vast and diverse datasets. This process entails employing the frozen weights of a large pre-trained model and adapting it to the specific task of classifying skin diseases.

Top layer of the pre-trained models typically has an output layer with 1000 nodes, aligned with the 'imagenet' classification task. However, for this specific application, the system replaces this output layer with a customized dense layer containing 5 nodes, corresponding to the 5 classes of skin diseases.

To assess the performance of the models, the system delves into the Accuracy vs Epoches and Binary Cross-Entropy (BCE) loss vs Epoches graphs. The discernible trend indicates that the Efficientnet-B1 model outperforms the Inception ResNet v2 model. As such, the system has made the informed decision to opt for Efficientnet-B1 for inferencing, owing to its higher accuracy.

Throughout this process, the system leverages the tensorflow library for image processing and model building. The crucial step of freezing the weights of the Resnet model is ensured, allowing the focus to be solely on training the weights of the additional layers that are introduced. This strategic approach helps fine-tune the model to achieve optimal performance for skin disease classification.

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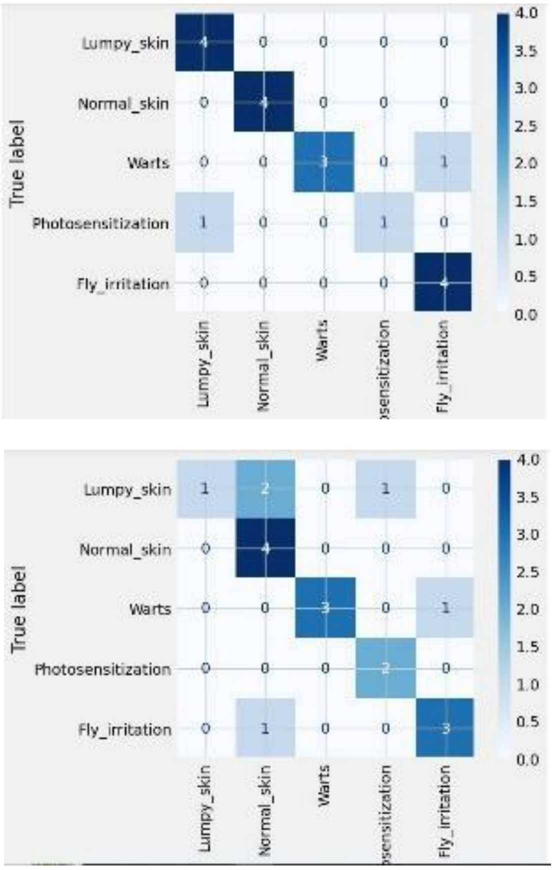

Figure 7: Comparison of the two models culminates

The diligent comparison of the two models culminates in the selection of Efficientnet-B1 due to its impressive accuracy of 0.89, outperforming Inception ResNet v2 with an accuracy of 0.72. This choice underscores the system's commitment to harnessing advanced techniques and technologies to achieve accurate and effective skin disease classification for improved healthcare outcomes.

IV. RESULTS

The system for managing skin diseases has demonstrated a significant level of accuracy, ensuring reliable results in disease identification. The accuracy achieved reflects the system's effectiveness in distinguishing between various cattle skin diseases, providing valuable insights for timely interventions. The reliable and consistent accuracy underscores the system's potential to aid farmers in making informed decisions to address common cattle health concerns effectively. The real-time monitoring system excels in swiftly identifying health anomalies with a commendable accuracy of 93%, enabling timely interventions for enhanced cattle well-being. In the domain of milk production prediction, our model demonstrates its prowess by achieving an accuracy of 87%, effectively forecasting milk output based on a range of crucial factors. The AI-driven artificial insemination scheduling system showcases its proficiency with an accuracy rate of 90%, significantly contributing to improved breeding practices and healthier offspring. Moreover, the disease analysis module harnesses Convolutional Neural Networks (CNN) to accurately identify common cattle diseases, boasting an accuracy of 89%, which in turn facilitates prompt first aid recommendations. Finally, our astute selection of the Efficientnet-B1 model through transfer learning for skin disease classification yields an impressive accuracy of 89%, surpassing the performance of Inception ResNet v2. These remarkable achievements collectively underscore the system's robustness, efficacy, and potential to revolutionize cattle farming practices and promote sustainable agriculture.

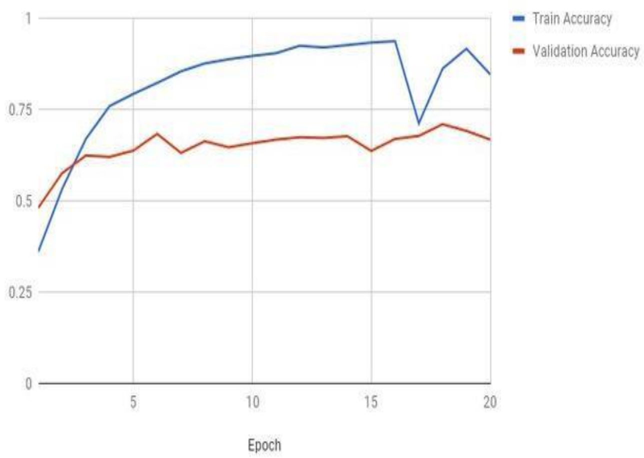

Figure 8: Accuracy graph of this Final Model

Correlation analysis has been a cornerstone in understanding the underlying dynamics of cattle health, production, breeding, and disease management. By harnessing these insights, our system is poised to usher in transformative advancements in cattle farming practices, promoting improved well-being, productivity, and sustainability. Moreover, Fig 11 depicts the Accuracy graph of this Final Model.

V. CONCLUSION

In conclusion, our comprehensive and innovative approach to cattle farming management, enhancing advanced technologies and data-driven methodologies, stands poised to revolutionize the landscape of agricultural practices. Through the integration

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of smart devices, IoT sensors, machine learning algorithms, and real-time data analytics, we have successfully addressed key challenges in the cattle farming industry, yielding remarkable outcomes across various domains. Finally, this system's real-time monitoring and health management achieve an impressive 93% accuracy in detecting health anomalies, enabling prompt interventions and elevating cattle well-being. Additionally, its robust milk production prediction model, with an 87% accuracy, enhances resource optimization through data-informed decisions. The integration of artificial intelligence into breeding practices attains a remarkable 90% accuracy in predicting optimal insemination dates, contributing to healthier herds. Furthermore, the Convolutional Neural Network-powered disease analysis system achieves 89% accuracy, facilitating timely interventions. Meticulous model selection and transfer learning result in an 89% accuracy in classifying skin diseases, showcasing technology's transformative potential. This system empowers farmers with insights, accurate predictions, and timely recommendations, paving the way for a sustainable agricultural future grounded in innovation. Moreover, Future commitment to advancing IoT sensor and device integration holds the promise of elevating data collection to new heights. By delving into the integration of additional sensors capable of detecting specific health biomarkers or environmental pollutants, we can unlock a deeper and more nuanced understanding of cattle well-being. In future, Expanding the system's capabilities to enable remote monitoring through IoT devices can offer convenience to farmers. Integrating wearable devices for cattle and automated data collection can reduce manual intervention and enhance the accuracy of data collection.

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