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Review Article

The Role of Artificial Intelligence and Machine Learning in Advancing Animal Biotechnology: A Review

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ABSTRACT

The integration of Machine Learning (ML) and Artificial Intelligence (AI) into animal biotechnology is revolutionizing the field, particularly in developing countries where agriculture and livestock play significant roles in the economy. AI and ML enable more efficient data analysis in areas such as genetic optimization, disease prediction, and livestock management, improving both productivity and sustainability. With the growing availability of data, AI-driven models can process large volumes of information from diverse sources such as environmental conditions, genetic markers, and health records, offering more precise insights than traditional methods. Recent advancements include AI-powered diagnostic systems for detecting and managing disease outbreaks, which allow for faster response times and more targeted interventions, ultimately reducing economic losses. Enhanced breeding techniques, now, leverage machine learning algorithms to predict desirable genetic traits, enabling farmers to make data-driven breeding choices. Feed efficiency improvements, another critical area, benefit from AI's ability to analyze nutrient requirements and optimize feeding schedules based on individual animal needs, reducing waste and costs. Additionally, AI is increasingly applied to animal health monitoring, using tools such as sound-based systems and piezoelectric sensors embedded in smart collars to track behaviors indicative of health issues. In the dairy sector, AI models assess health risks like nitrate contamination in milk, contributing to safer food production and improving public health. In genetic studies, AI enhances selective breeding, improving traits such as growth and disease resistance. This manuscript reviews the transformative role of AI and ML in animal biotechnology, focusing on developing regions where resource optimization is crucial. By simplifying complex techniques and providing step-by-step tutorials, this work aims to equip researchers and practitioners with practical tools to harness AI in animal biotechnology.

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1. Context

Animal biotechnology is transforming rapidly as a result of machine learning (ML) and artificial intelligence (AI), which offer new opportunities to boost output and address issues with animal health and breeding. The integration of AI and ML into biotechnology is crucial especially in developing countries where agriculture and livestock are vital to the economy. It enables the analysis of large amounts of genetic, health, and environmental data, which in turn helps improve breeding practices, disease diagnosis, and overall animal welfare. The use of AI to forecast disease outbreaks and increase feed efficiency has enormous potential to transform conventional methods and boost productivity and innovation in livestock management and research.

2. Data Acquisition

Animal biotechnology and veterinary science have benefited significantly from recent research conducted in developing nations, ranging from transgenic technologies to disease prevention strategies in livestock. For example, in the dairy industry, feeding propolis extracts has been demonstrated to influence milk composition and rumen microbial populations in Holstein cows, while novel approaches in transgenic animal technology highlight the use of nanoparticles and sperm-mediated gene transfer for improved animal breeding (3, 4). Recent research studies on *bovine mastitis* in Iran have revealed prevalent virulence factors like coagulase and fibronectin-binding proteins in *Staphylococcus aureus*, signifying their importance in vaccine development (6). The use of advanced molecular techniques has enhanced the detection of *Brucella* contamination in buffalo milk (8) and *Borrelia spp.* in small ruminants like sheep and goats, underscoring their role in the natural cycle of Lyme disease and *borreliosis* (10). Similarly, animal breeding research studies have revealed the enhanced desired traits and growth rates in Moghani crossbred lambs carrying the Booroola and myostatin genes, thereby demonstrating advancements in sheep breeding programs (12). Molecular methods and gene sequencing have led to identification of pyrethroid resistance in lice from goats, highlighting the need for integrated pest management strategies to combat pesticide resistance (14).

In the poultry industry, advancements in genetic tools have allowed for a deeper understanding of the genotype-phenotype relationship, improving breeding outcomes for broilers and layers (16). Significant developments in vaccination strategies for necrotic enteritis, a disease affecting poultry, have shown promising results particularly with recombinant chimeric vaccines targeting key toxins, which can provide an alternative to using antibiotics (18). Molecular characterization has revealed a high prevalence of β-lactamase-producing Enterobacterales in Iranian poultry and livestock slaughterhouse wastewater, which poses significant zoonotic risks (20).

A nested-PCR based study on wild animals, such as hares and hedgehogs, has revealed their roles as reservoirs for zoonotic pathogens, including *Borrelia spp*., adding another layer to wildlife conservation and management of tick-borne diseases (22). Gene expression studies, particularly in premature ovarian failure, have indicated that platelet-rich plasma (PRP) treatment could restore ovarian function by inhibiting apoptosis, offering new insights into reproductive health (24). Studies on venomous snakes have reported the presence of *Brucellaabortus*, marking the first such discovery in reptilian populations. Gene expression studies have also advanced, particularly in transgenic animal research and bioreactor development, such as the successful production of bovine chymosin in tobacco plants (26). Furthermore, the development of the nanoparticle-based Iribovax® COVID-19 vaccine demonstrates ongoing innovation in animal biotechnology, with applications extending beyond animal health to address global health challenges (28). These advancements in animal biotechnology can be further enhanced and optimized through the integration of artificial intelligence and machine learning, enabling more precise data analysis and predictions with reduced reliance on traditional experimentation.

Recent studies in machine learning (ML) and artificial intelligence (AI) have demonstrated their immense potential in animal biotechnology, improving everything from health monitoring to disease prediction. AI-powered technologies like sound-based systems and piezoelectric sensors, have been integrated into smart collars for continuous livestock health monitoring, allowing early detection of health anomalies (30). In dairy production, AI modeling has been applied to assess nitrate levels in cow milk, identifying significant health hazards for children and using algorithms like Gaussian Naive Bayes (GNB) and eXtreme Gradient Boosting (XGB) for accurate predictions (32).

In regenerative medicine, AI is improving scaffold design and accelerating the development of tissue engineering products by addressing challenges such as limited cell sources and improving tissue integration (33). AI is also playing a vital role in combating antimicrobial resistance (AMR), where deep learning and high-throughput screening have been used to discover new antimicrobial agents and predict resistance mechanisms (35). Furthermore, outbreaks of animal diseases, like foot-and-mouth disease (FMD), have been predicted in Iran using AI models, signifying high accuracy in disease management (37).

In cattle breeding, AI and ML have been used to identify significant single nucleotide polymorphisms (SNPs) for genomic selection, enhancing traits like growth and reproduction. Research studies employing ML algorithms like Random Forest (RF) and Gradient Boosting Machine (GBM) displayed higher accuracy over conventional approaches in predicting genomic breeding values (39). In addition, ML models have been employed to predict livestock emissions and optimize biogas production from manure, providing solutions to decrease greenhouse gas emissions.

Similarly, in ecological niche modeling in sheep, the MaxEnt machine-learning algorithm has been used to predict gastrointestinal nematode distribution across climatic zones, contributing to improved livestock management (42). Technological developments such as genome editing and next-generation sequencing (NGS) have further transformed bovine genomics, with projects like the 1000 Bull Genomes Project identifying SNPs crucial for improving milk and meat quality in cattle (44). These innovations emphasize the transformative power of AI and ML in advancing animal biotechnology across various fields.

This review provides an overview of the various applications of ML and AI in animal biotechnology, with a specific focus on making these concepts accessible and practical in the context of developing countries. Step-by-step tutorials are included to guide researchers, students, and practitioners in using AI tools for tasks such as animal genomics, diagnostics, and breeding optimization. By offering clear, simplified instructions and relevant case studies, the review aims to empower stakeholders to leverage AI-driven solutions for improving livestock productivity and health in environments where resource optimization is critical for sustainable development.

Animal biotechnology involves the application of scientific and engineering principles to improve and augment the genetics, reproduction, health, and overall productivity of animals. It aims to improve animal production, disease resistance, and the conservation of biodiversity through the use of techniques such as genetic engineering, cloning, and selective breeding. It comprehends a wide range of practices, from improving livestock and aquaculture efficiency to assisting wildlife conservation.

Figure 1 illustrates the role of Artificial Intelligence (AI) in revolutionizing various fields of animal biotechnology and how it contributes to enhanced growth and development. Broadly, the applications of animal biotechnology are categorized into three sectors: domestic animals, aquaculture, and forest animals. Each sector benefits from advanced biotechnological techniques, with AI serving as a critical tool for optimizing these processes.

In the animal biotechnology sector, AI is leveraged to improve the accuracy of genetic predictions, reduce generation intervals, and increase the intensity of selection in breeding programs. Techniques such as multiple ovulation, embryo transfer, twinning, and selfing, are improved through AI, leading to more efficient reproductive outcomes. AI also facilitates the detection of Economical Trait Loci (ETL), supports gene transformation, and aids in identification of potential candidate genes, all of which contribute to breeding livestock with desirable traits. These advancements ensure that livestock production becomes more efficient and sustainable. In aquaculture, AI assists in selective breeding, hybridization, and genetic marker-assisted selection to boost growth, disease resistance, and sex reversal. It also supports the cryopreservation of gametes and transgenic technology, which are essential for preserving genetic material and introducing desirable traits into aquatic species. AI-driven technologies streamline breeding techniques and improve disease control, ensuring a steady supply of healthy, high-quality fish stocks. Stock enhancement programs are further bolstered by AI's ability to monitor and predict growth patterns, resulting in more effective management of aquaculture resources. The application of animal biotechnology also extends to forest animals, where AI plays a crucial role in conservation efforts.

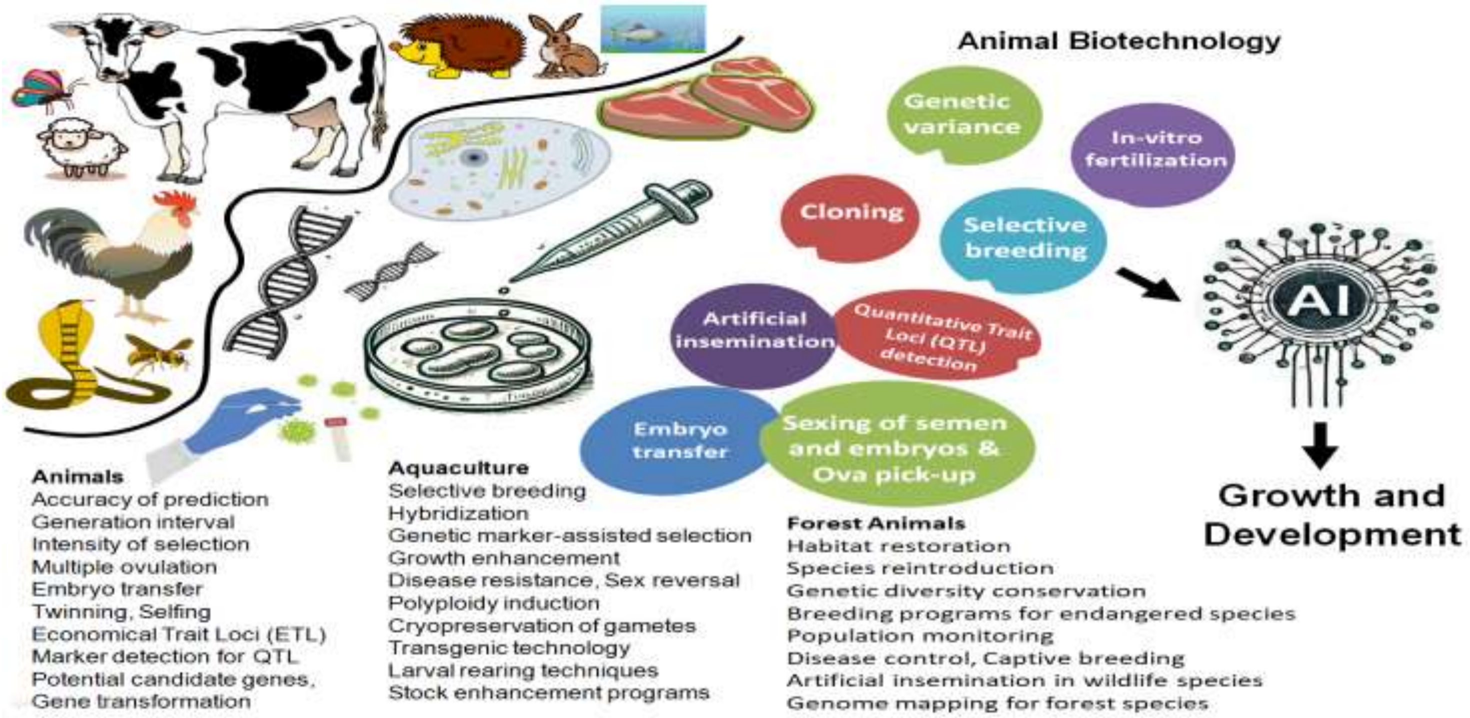

Figure 1. AI-Driven Animal Biotechnology for Enhanced Growth and Development.

Techniques like habitat restoration, species reintroduction, and genetic diversity conservation are made more efficient with AI, allowing for the protection of endangered species. AI facilitates breeding programs for species at risk, monitors population levels, and even aids in artificial insemination for wildlife species. AI's involvement in disease control, captive breeding, and genome mapping ensures that conservation efforts are both effective and sustainable, enabling the recovery of vulnerable wildlife populations.

At the core of these applications, AI enhances a variety of biotechnological processes, such as cloning, selective breeding, in vitro fertilization, and artificial insemination. By utilizing Quantitative Trait Loci (QTL) detection and advanced techniques like sexing of semen and embryos, AI helps optimize reproduction and genetic modification practices. The integration of AI in these biotechnological fields accelerates growth and development in livestock, aquatic species, and forest animals, ultimately promoting sustainable practices in agriculture, aquaculture and wildlife conservation.

3. Results

3.1 Artificial Intelligence and Machine Learning

Artificial Intelligence (AI) and Machine Learning (ML) are powerful technologies revolutionizing the way machines perform tasks that usually require human intellect. AI encompasses the goal of building systems capable of intelligent behaviors like reasoning, learning, and making decisions. ML, a specialized area within AI, focuses on creating algorithms that enable systems to learn from data and progressively improve without direct programming. By examining vast amounts of data, ML models can create trends, perform predictions, and adjust to new data autonomously. These capabilities are transforming fields such as healthcare, finance, robotics, and natural language processing by automating processes, enhancing decision-making, and revealing insights that traditional methods cannot. As these technologies advance, they are fostering unprecedented levels of innovation and efficiency across global industries.

The applications of artificial intelligence and machine learning algorithms in animal biotechnology can be broadly classified into three main categories (Figure 2). In animal biotechnology, the first main category is classification algorithms that are used to categorize data into predefined groups. For example, machine learning models can classify animals based on their genetic traits or disease susceptibility. A common example is predicting whether an animal is healthy or diseased based on certain biological markers or traits. The second category includes regression algorithms that are used to predict continuous

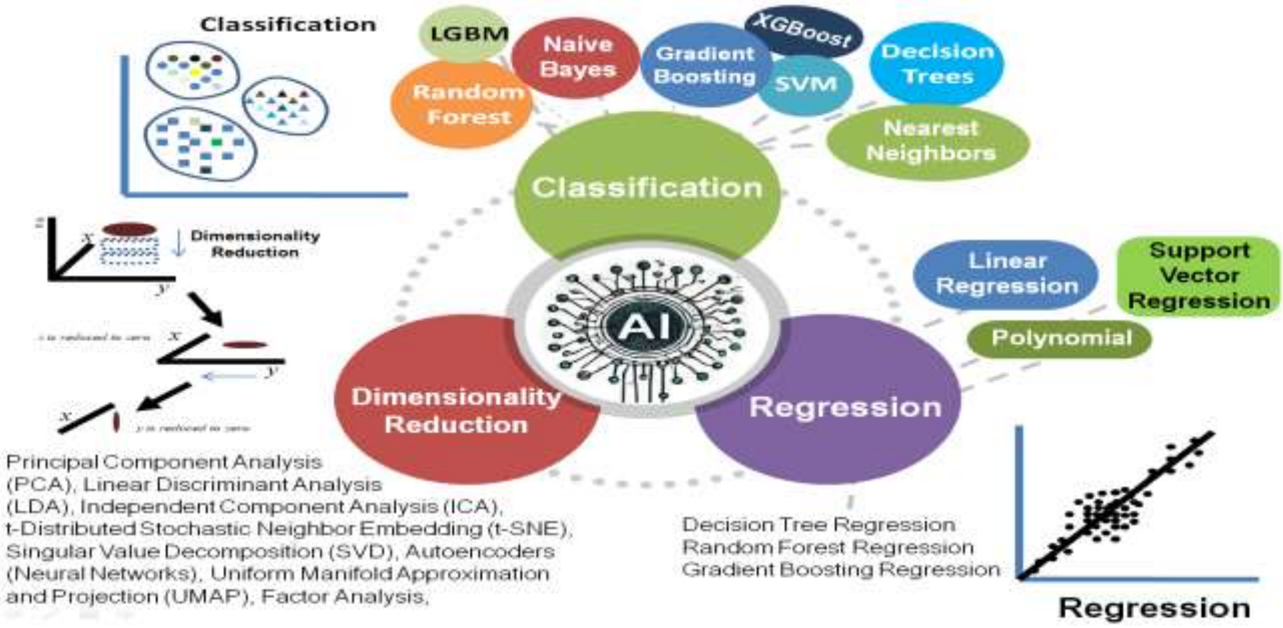

Figure 2. An Overview of Artificial Intelligence and Machine Learning Techniques in Classification, Regression, and Dimensionality Reduction.

outcomes in animal biotechnology. For instance, regression models can estimate the growth rate of animals or predict milk production based on factors such as age, nutrition, and genetic information. Another example is predicting the weight of an animal based on its breed and diet. The third category includes dimensionality reduction techniques that are used to simplify complex datasets by reducing the number of variables while preserving the most important information. In animal biotechnology, this can help researchers analyze genetic data with thousands of markers by focusing only on the most significant ones. For example, Principal Component Analysis (PCA) can be applied to genetic datasets to highlight key genetic variations while removing noise, making it easier to understand patterns in animal breeding or disease studies.

Figure 2 provides a comprehensive overview of the three core categories of machine learning algorithms used in artificial intelligence: classification, regression, and dimensionality reduction. It visually demonstrates how AI models can be categorized and applied based on the problem they aim to solve. Classification is explained with examples such as Naive Bayes, Random Forest, Support Vector Machines (SVM), Decision Trees, and other classification algorithms. These algorithms are used to categorize data into different classes or labels. The visual shows how classification techniques can separate data into distinct categories or clusters, making it possible to predict the category to which a data point belong.

For instance, Random Forest and SVM are popular classification techniques used for tasks like disease detection or image recognition. The diagram illustrates regression algorithms like Linear Regression, Support Vector Regression, Polynomial Regression, and Decision Tree Regression. These algorithms predict continuous numerical outcomes rather than discrete classes.

The regression graph is shown in the above diagram by fitting a line or curve to the data, enabling the prediction of values such as disease spread during a pandemic or optimizing process parameters in bioreactor data. Regression models estimate relationships between variables to make accurate predictions about future outcomes. Another diagram focuses on dimensionality reduction techniques, which are used to simplify large datasets with many features (dimensions) into smaller, more manageable ones. This is particularly useful for improving model efficiency and interpretability. The visual explains this concept by showing a 3D (Three-Dimensional) feature space being reduced to 2D (two-dimensional) and further to 1D (one-dimensional) if features are found to be correlated. The algorithms listed here, such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and t-SNE, help reduce the number of features while preserving the most important information in the dataset.

3.2 Machine Learning and Artificial Intelligence in Animal Biotechnology

As an example study to better understanding of the applications of machine learning in animal biotechnology, Mason et al. (2019) (47) used deep learning models to optimize therapeutic antibodies in mammalian cells by exploring a vast protein sequence space. They applied CRISPR/Cas9-mediated mutagenesis to generate site-directed mutagenesis libraries of the therapeutic antibody trastuzumab (Herceptin), followed by deep sequencing and flow cytometry to screen these libraries for antigen specificity. The models successfully predicted antigen-specific binding from a massive in silico library of ~10^8 variants, allowing them to identify highly optimized antibody sequences.

To implement the research work described by Mason et al. (2019) (47), a thorough understanding of deep learning, particularly Long Short-Term Memory Recurrent Neural Networks (LSTM-RNNs) and Convolutional Neural Networks (CNNs), as well as foundational concepts in mammalian cell biology, is essential. We will present the material in a simplified way that allows readers to gain practical knowledge in animal biotechnology and artificial intelligence applications, even with minimal prior experience.

The first step in this implementation process is setting up a suitable computing environment. Currently, Google offers a cloud computing service via Google Colaboratory, which provides a computing space with around 16GB RAM and 100GB hard disk for running machine learning applications. Figure 3 provides a step-by-step guide on how to access the Google Colaboratory environment through Google Drive, which is essential for running machine learning and artificial intelligence applications.

Step 1: Begin by logging into your Google Drive. Once inside, click on the option to create a New Folder. This folder will be used to store your Colaboratory projects and files.

Step 2: Name your folder (in this example, it's "Animal Biotechnology"). After typing the name, press the Create button to generate the folder.

Step 3: Once the folder is created, double-click on it to open and access the folder for the next steps.

Step 4: Inside your new folder, right-click to open a drop-down menu. From there, scroll down and click on Connect More Apps, which allows you to add additional functionalities to your Drive, including Google Colaboratory.

Step 5: In the search bar that appears, type "Colaboratory" to find the application.

Step 6: Once the Google Colaboratory app is displayed, click on the Install button to add it to your Drive. This is a one-time setup process.

Step 7: After the installation is complete, you can now right-click inside your folder again, go to More and select Google Colaboratory. This will create a new notebook where you can begin coding and running machine learning operations.

To effectively use this environment, it's advisable to spend at least a few days learning Python programming, focusing on basics such as variables, arithmetic operations, loops, lists, functions, and some critical libraries like Matplotlib, Numpy, and Pandas. Sample Python code for several applications can be found on platforms like Kaggle (48), which hosts pre-built code for various machine learning applications in animal biotechnology. Kaggle is owned by Google and is part of Google Cloud, providing data scientists and machine learning learners with tools and resources for collaboration.

Table 1 provides a comprehensive overview of various machine learning applications in animal biotechnology, hosted on Kaggle. It highlights different projects ranging from animal image classification to health condition assessment. These projects utilize advanced techniques such as deep convolutional neural networks (DCNN), transfer learning, and multiclass classification. The datasets are diverse, featuring thousands of images or records, and aim to solve real-world problems such as animal detection, shelter outcome prediction, and health diagnosis. Each project is linked to its corresponding Kaggle code (49), providing an accessible resource for those interested in exploring and implementing AI in the field of animal biotechnology.

3.3 Recent Advances in Applications of Machine learning and Artificial Intelligence in Animal Biotechnology

3.3.1. AI in Livestock Management

Accurate prediction of animal weight, which is crucial for improving the efficiency and sustainability of livestock management practices, often involves labor-intensive procedures and lacks instant and non-invasive solutions. The application of AI in livestock management eliminates the need for physical contact, improves animal welfare and also mitigates potential risks.

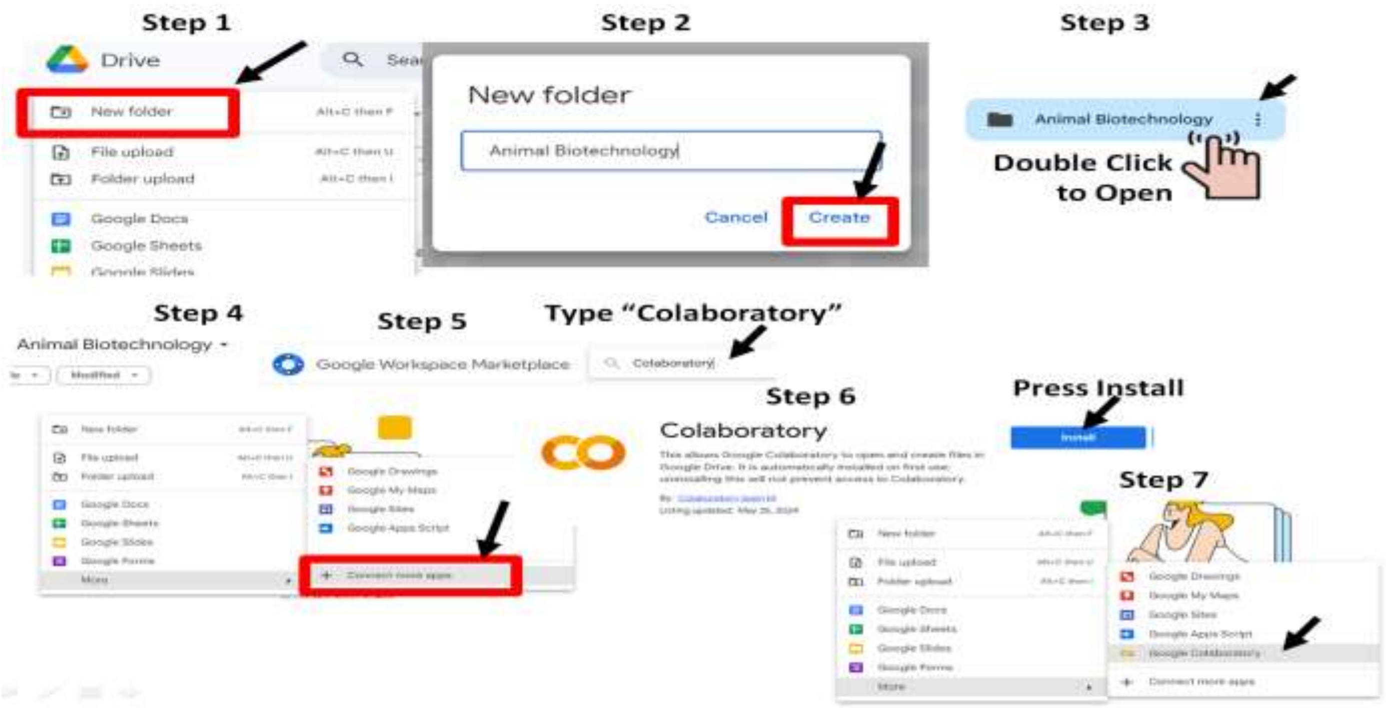

Figure 3. A step-by-step procedure to access Google Colaboratory environment for Machine Learning applications in Google Drive.

Table 1. Machine Learning Applications in Animal Biotechnology: Kaggle Resources.

Animal Biotechnology and Machine Learning	Kaggle Website URL
Animals Image Classification using Deep Convolutional Neural Networks (DCNN) and Transfer Learning: Animal image classification is a sophisticated artificial intelligence application used in fields like wildlife conservation, veterinary science, and agriculture. With advancements in deep learning and computer vision, it is now possible to analyze large sets of animal images with high accuracy.	https://www.kaggle.com/code/vencerlanz09/animal-image-classification-using-efficientnetb7
Animal Detection using Animal Dataset: The dataset contains 22,566 images across 80 animal classes. The data is preprocessed and visualized, followed by training a model that incorporates a pretrained architecture with added dense layers for animal detection. The model is trained to classify the diverse animal images effectively.	https://www.kaggle.com/code/nimapourmoradi/animal-detection
Predicting Shelter Outcomes for Cats and Dogs Using Multiclass Classification: The code contains multiclass classification to predict outcomes for shelter animals, specifically focusing on 4,800 cats and 6,656 dogs from the training dataset. Using the random Forest algorithm, the author aim to classify and predict the shelter outcomes for the animals based on the data provided.	https://www.kaggle.com/code/mrisdal/quick-dirty-randomforest
Animal Condition Classification Dataset and Exploratory Data analysis. The dataset is designed to assess animal health across various species by analyzing five distinct symptoms (1. Fever, Fetopelvicdisproportion, other types 2. Diarrhea, Difficulty in breathing, 3. Coughing, Vomiting, 4. Weight loss, Death, 5. Pains) to determine if an animal's condition is dangerous. It includes a diverse array of animals, offering potential to develop predictive models that cross species lines.	https://www.kaggle.com/datasets/gracehephzibahm/animal-disease

Table 2 presents recent applications of machine learning in livestock management. These studies explore various AI-driven models to address key challenges in livestock farming. For instance, machine learning algorithms have been employed to forecast livestock supply and outputs, automatically classify cow behavior, and predict livestock weight. In the area of genomics, machine learning models have been utilized to identify cattle breeds using SNP panels, showcasing their potential for advancing livestock genetics. Overall, the studies highlight the power of AI in optimizing farming processes, reducing costs, and improving sustainability in livestock production.

3.3.2. Genetics and AI

Table 2 also illustrates recent advancements in using machine learning within animal genetics,

Table 2. Applications of Artificial Intelligence and Machine Learning in Animal Biotechnology.

Description	Citation
Applications of machine learning in livestock management	
Analyzing Internal and External Factors in Livestock Supply Forecasting: This study uses machine learning algorithms to predict future livestock values, focusing on sustainability in the pork market.	(1)
Predictive Models for Livestock Output: This research applies machine learning techniques to predict livestock outputs, utilizing various predictors such as livestock units and costs to improve forecasting.	(2)
Predicting the Weight of Livestock: A machine learning model that utilizes algorithms like Random Forest and Ridge Regression to predict livestock weight based on different input features.	(5)
Applications of machine learning in the field of animal genetics	
Identification of Potential Feature Genes for Drug Efficacy in Non-Alcoholic Steatohepatitis Animal Model: This study uses machine learning algorithms to identify key genes that predict treatment responses, focusing on genetic and epigenetic RNA markers in an animal model.	(7)
Genomic Prediction of Cow Behavioral Traits Using Machine Learning: This research focuses on predicting behavioral traits in Holstein cattle, using data from automated milking systems and machine learning models to enhance genetic selection.	(9)
Genomic Prediction in Chickens Using Bioinformatics and Machine Learning: Integrating bioinformatics and machine learning, this research aims to predict genetic pathways in chickens, identifying crucial genes related to growth and other traits.	(11)
Recent advances in animal cloning coupled with machine learning	
Serine Protease Inhibitor Identification Using Machine Learning: This research utilized machine learning strategies to identify and analyze serine protease inhibitors, key proteins that play a role in cloning experiments in the animal's physiological context.	(13)
In-Silico Cloning for Vaccine Constructs against Bovine Coronavirus: This study applied machine learning for immunogenic epitope mapping and in-silico cloning to expedite the creation of vaccine constructs, focusing on expression vectors for animal applications.	(15)
Mapping Protective Precision Vaccines using Machine Learning: Researchers applied machine learning to structural proteomics and in-silico cloning to develop precision vaccines for *Mycoplasma pulmonis*, optimizing the vaccine before animal testing.	(17)
The integration of AI & ML in embryo transfer technologies	
Time-lapse Imaging to Differentiate Embryos: This study uses machine learning algorithms to analyze time-lapse imaging and differentiate embryos from young and old mice for more efficient embryo transfer, with or without preimplantation genetic testing.	(19)
Spectroscopy and Machine Learning for Bovine Embryo Grading: The research focuses on integrating imaging, spectroscopy, and machine learning models to automatically predict embryo quality, aiming to improve pregnancy success rates in bovine embryo transfer.	(21)
AI-Assisted Embryo Selection in Newts: This study developed an AI-assisted system for selecting viable embryos in Iberian ribbed newts, which is used for fetal development toxicity testing in embryo transfer technologies.	(23)
Selective Breeding and AI	
Machine Learning for Genomic Selection in Pacific White Shrimp: This study evaluates machine learning methods for genomic selection, focusing on growth traits in Pacific white shrimp, enhancing selective breeding programs.	(25)
Machine Learning and Survival Traits in Olive Flounder: This study compares machine learning models with traditional methods for genomic selection related to viral resistance traits in olive flounder, enhancing survival traits.	(27)
Bioinformatics in Animal Breeding: A review discussing the integration of bioinformatics and machine learning in animal breeding and genetics to enhance the accuracy of selective breeding programs.	(29)
Machine Learning Techniques for Enhancing Accuracy of prediction	
Prediction of Growth and Feed Efficiency in Mink: This study applies machine learning algorithms to predict growth and feed efficiency traits in mink, enhancing the accuracy of predictions for selective breeding programs.	(31)
Genomic Prediction of Cow Behavioral Traits: Machine learning methods, including CNN and MLP, are used to predict cow behavioral traits in Holstein cattle, achieving moderate accuracies, with CNN showing the highest accuracy.	(9)
Animal Healthcare and Diagnostic Accuracy: A review on the role of machine learning in animal healthcare, emphasizing its ability to improve diagnostic accuracy in various animal health-related applications.	(34)
Aquaculture and AI	
ANN Algorithm	
Random Forest: Used to identify aquaculture ponds and optimize aquaculture area management	(36)
Deep Learning: Image dataset for fish disease detection to ensure aquaculture health	(38)
Decision Trees: AI-based fish growth prediction and optimization of water quality	(40)
Artificial Intelligence and Machine Learning in forest animals	
Study examining vertical foraging niches in mammals and birds using functional traits and phylogenetic data to understand ecological and evolutionary patterns.	(41)
Deep learning-based model called Deep Indel for predicting outcomes of CRISPR/Cas9 genome editing with improved accuracy and interpretability.	(43)
Research on the local adaptation of Aedesaegypti mosquitoes, highlighting genomic variations linked to environmental conditions.	(45)
Investigation of microbial compositions in ticks from neotropical forest fragments, analyzing intrinsic and extrinsic factors influencing microbiome structure.	(46)

showcasing AI's transformative potential in genetic research. Through the application of machine learning models, scientists can analyze extensive datasets to forecast genetic traits, enhance breeding programs, and boost disease resistance. These studies span a range of applications—from predicting genomic traits in livestock like cattle and chickens to pinpointing crucial genes within animal models—highlighting AI's vital role in accelerating research progress and improving accuracy in livestock management. Machine learning supports the discovery of intricate patterns and associations within genetic data, making it a critical tool for enhancing breeding program efficiency and promoting progress in animal biotechnology. The integration of AI in genetic research not only drives productivity but also supports sustainable agriculture and the preservation of important genetic resources in animal populations.

3.3.3. Animal Cloning and AI

Animal cloning, combined with artificial intelligence (AI) and machine learning (ML), is transforming the field of biotechnology by enhancing precision and efficiency in various applications. As seen in recent studies (Table 2), machine learning has been applied to identify key proteins, streamline the cloning process in vaccine development, and enhance mutation mapping in genetic studies. For example, AI was utilized to analyze serine protease inhibitors in animal models, while in-silico cloning and vaccine design have benefited from machine learning tools, accelerating research without the immediate need for animal trials (13, 15). The ability of machine learning to handle complex datasets allows for accurate predictions, improving the efficiency of identifying genetic mutations and optimizing vaccine formulations before animal testing. These advancements not only speed up research but also reduce ethical concerns surrounding animal cloning by minimizing the use of live animals in experimental stages. The integration of AI and ML into cloning processes is pivotal in making animal biotechnology more sustainable and effective in solving real-world challenges in genetics and disease control.

3.3.4. Embryo Transfer and AI

Embryo transfers, especially in the cattle industry, which involves the visual inspection and selection of embryos by embryologists, suffer from inaccuracies, inconsistencies in the manual grading of bovine embryos and the non-availability of embryologists. The integration of machine learning in embryo transfer technologies represents a significant advancement in animal biotechnology. Various applications (Table 2), such as using time-lapse imaging to distinguish between embryos from younger and older mice, are now enhanced by machine learning models that improve the accuracy of embryo selection (17, 19).

In bovine reproduction, spectroscopy and video microscopy, combined with machine learning algorithms, are enabling more precise predictions of embryo viability and transferability, enhancing pregnancy success rates (21). These AI-driven systems are not just limited to cattle; they are being applied to other species, such as Iberian ribbed newts, for more specialized applications like embryo-fetal development toxicity testing (23). By integrating advanced data analytics, these studies are paving the way for more informed, data-driven decisions in the embryo transfer process, reducing failures and improving overall efficiency in reproductive technologies.

3.3.5. Selective Breeding and AI

Although modern genotyping technologies have transformed genomic selection in animal breeding, the large marker datasets have numerous drawbacks in terms of flexibility, accuracy, and computational power. The applications of ML models in animal breeding offer promising solutions due to their great flexibility and their ability to capture patterns in large, noisy datasets. The integration of machine learning into selective breeding and genomic studies is revolutionizing animal breeding (Table 2), enhancing the precision of selecting traits such as growth, survival, and resistance to diseases. Studies show how machine learning models can be applied to predict growth traits in Pacific white shrimp, improve survival traits in olive flounder, and estimate genetic parameters in insect production, all contributing to more efficient breeding programs (25, 27). The application of AI and machine learning in bioinformatics also streamlines genomic data analysis, making selective breeding more effective across various animal species. These innovations are particularly crucial in optimizing animal health and productivity while advancing sustainable agricultural practices (29).

3.3.6. Accuracy of Prediction in Animal Biotechnology and AI

Table 2 showcases the critical role of machine learning in enhancing the accuracy of predictions in various fields of animal biotechnology. Machine learning models are used for a wide range of applications (Table 2), such as predicting growth and feed efficiency in mink, where improved accuracy aids selective breeding efforts (31). Conventional methods of measuring feed intake and body weight of individual animals are time-consuming, labor-intensive, stressful and expensive. Alternatively, Machine learning applications propose a cost-efficient approach to address these limitations. In Holstein cattle, algorithms like CNN and MLP have been applied to predict behavioral traits, with CNN achieving the highest accuracy (9). Similarly, machine learning enhances diagnostic capabilities in animal healthcare by improving prediction models for disease detection. The accuracy of predicting carcass yields in broiler chickens has also been explored, revealing variations across different machine learning algorithms (34). Overall, these advancements underline the significant impact of AI and machine learning in improving the efficiency and accuracy of various animal biotechnology processes.

3.3.7. Aquaculture and AI

Table 2 provides a comprehensive overview of how machine learning techniques are applied across various species in aquaculture to optimize growth, enhance health monitoring, and improve system efficiency. For example, random forest algorithms have been used in China's inland lake aquaculture to identify and manage aquaculture ponds, helping to maximize resource use and reduce environmental impact. Similarly, non-invasive fish biometric techniques combined with machine learning have been applied to various species to predict biomass and improve farm management practices, making aquaculture more efficient and sustainable (36). Early detection of fish diseases, which is crucial, in aquaculture, employs methods that are often costlier, time-consuming, and invasive. Alternatively, machine learning approaches are rapid, accurate, and non-invasive. Another critical area of application is in water quality management and fish health monitoring. Techniques such as support vector machines (SVM) and ensemble methods have been used to predict water contamination and identify critical water parameters for aquaculture ponds. These machine learning approaches ensure that aquaculture systems maintain optimal water conditions, improving survival rates and reducing the risk of disease outbreaks. CNNs and random forest models have also been applied to the detection of fish diseases, such as in salmon farming, where image datasets were used to diagnose health conditions in real-time, reducing mortality rates (38). The integration of machine learning in predictive modeling for species-specific growth has proven particularly valuable. For instance, shrimp farming has benefited from machine learning models that predict shrimp growth, enabling aquaculture operators to optimize feeding regimes and minimize costs. Lobster farming has seen improvements through IoT-based models that forecast water quality, ensuring the health and growth of the species (50). Across all these applications, machine learning serves as a critical tool in driving efficiency, sustainability, and innovation within the aquaculture industry.

3.3.8. Forest Animals and AI

The application of artificial intelligence (AI) and machine learning (ML) in monitoring forest animals has emerged as a transformative tool in wildlife conservation and biodiversity management (Table 2). For instance, the use of phylogenetic trees in the study by Jantz et al. (2024) (41) demonstrates the combination of bioinformatics and AI to predict vertical foraging niches in terrestrial mammals and birds. This approach allowed researchers to utilize functional traits and phylogenetic data, processed through machine learning models, to understand how evolutionary patterns influence animal behavior in forest ecosystems. By applying ML techniques, they could analyze complex ecological relationships and generate insights into how specific traits, such as diet and body mass, correlate with vertical foraging strategies, showing the significant role of AI in deciphering ecological data at a deeper level.

In another study (Table 2) by Zhang et al. (2024) (43), deep learning models like BERT were employed in the DeepIndel framework to predict CRISPR/Cas9 genome editing outcomes, showcasing how AI and biotechnology can intersect to improve genetic manipulation techniques. The utilization of advanced machine learning algorithms in this research highlights the potential for AI to enhance biotechnological applications, including gene editing and precision breeding in species that inhabit forest environments. Furthermore, the use of stable isotope analysis to study dietary shifts in wild mountain gorillas is a method that could benefit significantly from the integration of machine learning for more accurate pattern detection and data interpretation. Bennett et al. (2021) (45) focused on the local environmental adaptation in *Aedes aegypti* mosquitoes, highlighting how genomic variations are linked to environmental factors like climate and vegetation, which can also be analyzed using AI tools to predict changes in disease dynamics and vector behavior in forest regions. Kueneman et al. (2021) (46) examined tick microbiomes in neotropical forest fragments, showing that intrinsic factors such as tick species and life stage played a crucial role in microbiome composition, a finding that could be further analyzed using AI to understand microbial interactions better. While these studies indicate the progress made in applying AI and biotechnology in forest animal research, there is still a vast amount of work to be done to fully explore and utilize AI's potential in this area, particularly in developing new biotechnological approaches that are specifically tailored to the unique challenges posed by forest ecosystems and their inhabitants. The diversity of these applications underscores the importance of AI and ML in enhancing the efficiency and accuracy of forest animal monitoring, and highlights their role in preventing habitat loss, maintaining biodiversity, and ensuring the sustainability of ecosystems.

4. Conclusion

The rapid evolution of machine learning and artificial intelligence in animal biotechnology marks a significant shift toward more efficient, data-driven approaches to managing livestock and improving agricultural productivity. Traditional methods employed in various domains of Animal Biotechnology, often involve procedures that are time-consuming, expensive, labor-intensive, stressful, and inconsistent, and they lack instant and non-invasive solutions. The application of AI and ML in Animal Biotechnology not only enhances traditional methods but also provide novel solutions for challenges such as disease detection, breeding optimization, environmental sustainability, and reducing failures and costs as well as improving efficiency. AI-powered systems that integrate sensors, data analytics, and real-time monitoring allow for more precise management of animal health and welfare, reducing the time and resources required for effective disease control and livestock management. This is especially relevant in developing countries, where agriculture plays a crucial role in the economy, and technological advancements are key to achieving food security. In addition to improving disease detection and management, AI and ML play a pivotal role in optimizing genetic selection. Advanced ML algorithms have enabled researchers to analyze vast genetic datasets, identify critical genetic traits, and enhance breeding programs. For instance, studies on bovine genomics and poultry genetics demonstrate how ML can predict desirable traits, leading to more productive and resilient livestock. Moreover, AI-driven genome editing tools, such as CRISPR, are paving the way for innovations in animal biotechnology, improving both the quality and efficiency of breeding programs.

Another vital area of AI application is sustainability in livestock management. Through ML models, researchers have developed tools to predict livestock emissions, optimize biogas production, and mitigate environmental impacts. AI also aids in water quality management in aquaculture, ensuring optimal conditions for fish farming, while minimizing resource waste. As the agricultural sector continues to face challenges related to climate change, AI technologies will play an increasingly important role in adapting to these environmental pressures, ensuring more sustainable and resilient food production systems. Overall, the advancements in AI and ML are transforming animal biotechnology across various fields, from livestock health management to genetic research and sustainable farming. By harnessing the power of AI, researchers, farmers and policymakers can develop more efficient and sustainable practices that contribute to global food security and animal welfare. The continued integration of these technologies, particularly in developing regions, will be instrumental in overcoming current and future challenges in agriculture, making animal biotechnology a critical area for innovation and progress.

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Authors' Contribution

Study concept and design: S.K.R.R.
Acquisition of data: S.K.R.R, D. P.
Analysis and interpretation of data: S.K.R.R, D. P.
Drafting of the manuscript: S.K.R.R.
Critical revision of the manuscript for important intellectual content: D. P.
Statistical analysis: D. P.
Administrative, technical, and material support: D. P, S.K.R.R

Ethics

As no human or animal subjects were involved in this study, and the data were collected from previous studies conducted in the world, ethical committee approval was not required.

Conflict of Interest

The authors declare that they have no conflict of interests.

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Data Availability

The data that support the findings of this study are available on request from the corresponding author.

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