Relating different Artificial Intelligence approaches for Animals disease outbreak detection

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Abstract: The past two years have witnessed a worrying surge in animal disease outbreaks, with African swine fever, foot-and-mouth disease, and bird flu wreaking havoc on animal populations and human livelihoods. Millions of animals have succumbed to these highly contagious diseases, causing severe economic losses, disrupting livestock industries, and threatening global food security. Data reveals the alarming occurrence, distribution, and impact of these outbreaks, while highlighting the challenges in controlling them and the potential public health risks. Innovative approaches like AI-powered disease models and international cooperation are crucial to tackle this crisis and mitigate future threats. The abstract is about finding disease outbreak of different natures, so we can predict it before it is going to hit in future.
By integrating existing information with the potential of cutting-edge solutions of Artificial Intelligence and Machine learning, our models of SVM with accuracy and precision of 0.9041%, recall 1.0 and ROC AUC of 0.05. The confusion matrix indicates 0 true positive predictions and 0 false negative predictions. These are the models used and results are mentioned respectfully. KNN with accuracy of 99%, precision of 1.0, Recall 0.99% and ROC AUC of 0.99%. The confusion matrix indicates 489 true positive predictions and 4 false negative predictions Naive Bayes with accuracy of 0.99, precision of 1.0, recall and ROC AUC 0.99. The confusion matrix indicates 489 true positive predictions and 37 false negative predictions.

Keyword: Artificial Intelligence, Machine Learning, Animal Disease, Predications, Naïve Bayes, KNN, SVM.

1. INTRODUCTION

Animal diseases remain a significant threat to animal well-being, food safety, national economies, and the environment, despite advancements in vaccines and biosecurity measures [1]. Increased global travel, higher livestock production, and climate change have amplified the risk of devastating animal losses from infectious diseases. The past two years have witnessed a troubling rise in outbreaks of highly contagious diseases like African swine fever, foot-and-mouth disease, and bird flu, leaving a trail of destruction in their wake [3]. These outbreaks highlight the critical need for improved surveillance, prevention strategies, and international collaboration.

African swine fever has emerged as a major global threat, causing severe economic losses and jeopardizing food security [4]. The data reveals a rapid spread of the disease, with a high number of cases reported across various regions. The lack of effective treatments or vaccines has hampered control efforts, leading to substantial pig population losses and disruptions in the pork industry [4].Foot-and-mouth disease, another highly contagious illness, poses a significant risk to livestock worldwide, as evidenced by the global distribution of outbreaks [5]. The economic repercussions extend beyond animal losses, as trade restrictions and control measures disrupt livestock movement, impacting farmers and agricultural industries [6].

Climate change may potentially contribute to the increased prevalence of animal diseases [7].Advancements in artificial intelligence (AI) have brought forth the development of algorithms for disease detection and chemical toxicity prediction, leveraging large databases and extensive animal testing [8]. AI tools have facilitated disease diagnosis, accurate predictions, and understanding of complex biological structures, risk analysis, and targeted treatments with anticipated effects [8]. The integration of AI with other fields, like biomedicine, and the abundance of healthcare data have further propelled recent breakthroughs [7]. However, larger animals with more physiological similarities to humans remain better models for studying certain diseases, such as cardiovascular disease, where zebrafish, rats, dogs, and pigs are commonly used [5].

The recent surge in animal disease outbreaks, with their devastating impact and crippling economic consequences, necessitates immediate action on a global scale [12]. Diseases like African swine fever, foot-and-mouth disease, and bird flu have not only decimated livestock populations but also exposed vulnerabilities in our current surveillance and prevention systems, raising concerns about food security [12].

We are not without defenses. By effectively utilizing existing data and adopting a multifaceted approach, we can start to gain control. The first line of defense lies in strengthening surveillance systems. This entails expanding geographical coverage, enhancing detection capabilities through cutting-edge technologies, and fostering effective communication networks among local communities, veterinary services, and international agencies. Early detection is crucial to prevent outbreaks from spiraling out of control and allows for swift containment measures.

Prevention goes beyond early detection. Proactive approaches, driven by comprehensive data analysis, hold immense potential. Researchers can develop targeted vaccination campaigns, implement region-specific biosecurity protocols, and even explore advanced genetic techniques to breed disease-resistant livestock by identifying hotspots and analyzing risk factors. We must shift our focus from merely reacting to outbreaks to actively preventing them from occurring in the first place.

This endeavor requires a concerted effort from a diverse range of stakeholders. Governments must play a crucial role by providing essential resources, enacting and enforcing robust biosecurity regulations, and supporting research initiatives. Veterinary professionals have the responsibility of educating farmers, implementing prevention strategies on the ground, and remaining at the forefront of disease diagnostics and treatment. Farmers themselves need to be empowered with knowledge and resources to maintain biosecurity measures within their operations and report any suspicious symptoms promptly. Additionally, international cooperation is vital. Openly sharing data, expertise, and best practices across borders can significantly enhance our collective preparedness and enable coordinated responses to outbreaks.

The current state of animal disease outbreaks demands decisive action. By harnessing data, implementing comprehensive prevention strategies, and fostering collaboration among stakeholders, we can safeguard animal populations, human well-being, and food security. This is not just a technical challenge but a collective responsibility – a fight we must wage together to prevent animal disease outbreaks from disrupting the delicate balance of our global ecosystem [13].

2. LITERATURE REVIEW

Every day, a silent but potent threat casts a shadow across the delicate web of life – the specter of transboundary animal diseases. These invisible adversaries pose a danger not just to the lives of our animal companions, but to the very fabric of our societies. In recent times, the world has witnessed a chilling rise in the number of such outbreaks, each leaving a trail of devastation and amplifying the urgent need for a unified response.

The implications of these outbreaks extend far beyond immediate animal losses. Their tendrils reach into the very heart of our livelihoods, food security, national economies, and even global markets. The specter of zoonotic diseases, capable of leaping from animals to humans, adds another layer of vulnerability, raising the chilling possibility of human pandemics. This stark reality demands a paradigm shift in our approach – a move towards a comprehensive and coordinated One Health strategy [14]. At the core of this strategy lies the triumvirate of early warning, early detection, and early response. These are not mere buzzwords, but critical steps in severing the chain of transmission before it can engulf entire populations. Imagine a future where:

Advanced surveillance systems, powered by data analytics and artificial intelligence, scour the globe for the faintest whispers of emerging threats. Real-time disease mapping and risk assessment become commonplace, allowing proactive interventions to be deployed at the first flickers of an outbreak. Veterinarians equipped with next-generation diagnostic tools can rapidly pinpoint the culprit with pinpoint accuracy, ensuring swift and effective treatment before the disease gains a foothold. Imagine handheld biosensors capable of identifying pathogens within minutes, or drones patrolling vast landscapes, their thermal imaging eyes detecting subtle changes in animal behavior [15].

Preparedness plans, carefully calibrated and rehearsed, spring into action with clockwork precision. Quarantine measures are implemented swiftly, ensuring the disease remains contained within a defined perimeter. Vaccination campaigns are tailored to the specific pathogen, bolstering herd immunity, and forming a protective shield against future waves of infection.

But this proactive approach requires addressing the very roots of the problem. We must acknowledge the role of unsustainable agricultural practices, where intensive farming methods create breeding grounds for pathogens and weaken animal immune systems. The unregulated movement of animals and animal products, across both borders and within countries, must be carefully monitored and controlled to prevent the inadvertent transport of disease. The ever-growing network of global travel and trade necessitates robust international cooperation, with information sharing and coordinated action becoming the norm, not the exception. Finally, the ever-shifting landscape of climate change, disrupting ecosystems and altering migratory patterns, demands our attention, as new disease risks may emerge from this evolving reality [16].

The battle against transboundary animal diseases is a collective one, a marathon, not a sprint. By embracing the One Health approach, weaving together the threads of animal health, human health, and environmental sustainability, we can build a brighter future. One where early warning signals echo across borders, early detection becomes a seamless process, and early response forms an impregnable shield against these invisible foes. Let us join hands, scientists, veterinarians, policymakers, and citizens alike, to ensure that the shadow of transboundary animal diseases fades into the light of proactive preparedness and global cooperation. For the well-being of our animal companions, the safety of our communities, and the security of our world depends on it [17].

The welfare of livestock populations is not just a matter of compassion – it's vital for safeguarding the food security and livelihoods of millions around the world. But a lurking shadow threatens this delicate balance: the constant specter of animal diseases, including those capable of leaping to humans, known as zoonotic diseases. This is where the Food and Agriculture Organization's Emergency Prevention System (EMPRES) steps in, playing a crucial role in connecting local knowledge and global expertise to combat these invisible adversaries[18].

Established in 1994, EMPRES operates not just as a reactive force, but as a proactive shield. Its mission is twofold: to assist countries in preventing and controlling the world's most serious livestock and zoonotic diseases, while simultaneously keeping vigilant watch for the emergence of new pathogens. This is not a solitary endeavor. EMPRES fosters close collaboration with member countries, regional and international organizations, and research centers. This intricate web of partnership allows for:

Early Warning: EMPRES acts as a vigilant sentinel, constantly analyzing data and monitoring trends to provide member countries with timely alerts about potential outbreaks. This early warning system buys precious time for preventative measures to be implemented, potentially averting disaster before it unfolds.

Technical Guidance: Beyond the alarm bell, EMPRES offers invaluable technical expertise. They provide detailed guidance on risk management strategies, tailored to specific transboundary threats and regional contexts. This includes assisting with the development and implementation of robust biosecurity measures and control programs for high-impact diseases like foot-and-mouth disease and African swine fever [19].

One Health Approach: Recognizing the interconnectedness of animal and human health, EMPRES champions the One Health approach. This philosophy necessitates coordinated efforts across various sectors, ensuring that animal health interventions contribute not only to livestock security but also to the well-being of human communities.

Capacity Building: To ensure long-term success, EMPRES empowers countries to build and strengthen their own animal health and biosecurity capabilities. This is achieved through training programs, technical assistance, and the facilitation of knowledge exchange between experts and local communities [20].

This multi-pronged approach forms the backbone of EMPRES's remarkable impact. Since its inception, it has contributed to:

Reduced outbreaks: By equipping countries with the tools and knowledge to prevent and control diseases, EMPRES has actively curtailed the spread of numerous animal scourges, protected livestock populations and ensuring food security for vulnerable communities.

Enhanced One Health collaboration: EMPRES has fostered closer cooperation between animal health professionals, human health experts, and environmental specialists, breaking down silos and enabling a more holistic approach to tackling zoonotic diseases.

Improved surveillance and response: Through strengthened networks and early warning systems, EMPRES has allowed for faster detection and more effective response to emerging threats, minimizing the devastating impact of disease outbreaks [21].

However, the battle against animal diseases is far from over. New pathogens constantly emerge, and existing threats adapt and evolve. Therefore, EMPRES remains actively involved in:

Research and development: Continuous research into novel diagnostic tools, effective vaccines, and innovative control strategies is crucial to stay ahead of evolving threats. EMPRES actively supports and collaborates in such research endeavors, ensuring the most cutting-edge solutions are readily available to member countries.

Strengthening global response mechanisms: Effective disease control requires international cooperation. EMPRES works tirelessly to foster collaboration between countries and organizations, promoting harmonized standards and streamlined response protocols for a unified global defense against animal diseases.

The challenges we face are significant, but with the dedication and expertise of organizations like EMPRES, we can build a future where livestock populations thrive, food security is ensured, and the risks of zoonotic diseases are minimized. By connecting local knowledge and global expertise, fostering collaboration, and constantly pushing the boundaries of research and innovation, EMPRES stands as a vital shield, protecting not just the well-being of animals but the health and prosperity of entire societies [22].

Ensuring robust animal health systems requires not just swift responses to outbreaks, but a strong foundation of knowledge and expertise within each nation. Recognizing this, the Food and Agriculture Organization's Emergency Prevention System (EMPRES) dedicates a significant portion of its efforts to capacity building, empowering countries to navigate the complex landscape of animal disease prevention and control.

Central to this endeavor are diverse capacity development initiatives, tailored to equip veterinary professionals and policymakers with the tools and skills they need to protect their livestock populations and safeguard public health. These initiatives go beyond theoretical knowledge, bridging the gap between science and practical application.

One cornerstone of this capacity building is the In-Service Veterinary Applied Epidemiology Training (ISAVET) program. Imagine a program that transforms veterinary graduates into skilled disease detectives, honed to identify, investigate, and manage outbreaks with precision. ISAVET does just that, through an immersive blend of classroom learning, field exercises, and real-world mentorship. This intensive training prepares veterinarians to play a vital role in national surveillance systems, ensuring early detection and rapid response to potential threats.

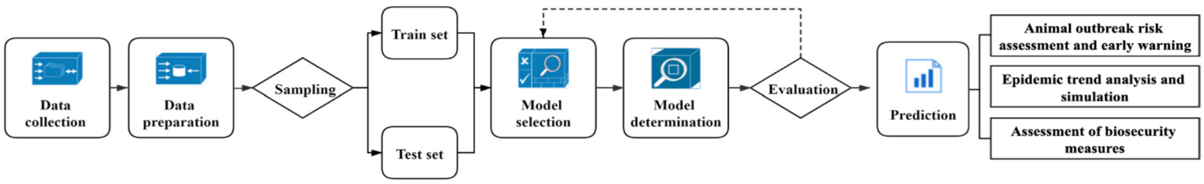
But knowledge dissemination extends beyond ISAVET. Seven strategically located regional and sub-regional virtual learning centers serve as hubs for continuous education. Imagine a network of online classrooms, accessible to professionals across continents, offering a diverse range of courses. These courses tackle vital topics, from risk assessment and surveillance techniques to biosecurity protocols and One Health implementation. This democratization of knowledge empowers participants to become agents of change within their own countries, effectively translating acquired skills into tangible improvements in animal health systems.

EMPRES's commitment to empowerment goes beyond virtual classrooms. Country missions serve as a testament to this proactive approach. Imagine a team of experts, armed with specialized knowledge and practical experience, arriving in a nation seeking to strengthen its disease control protocols. Through collaborative workshops, on-site training, and tailored guidance, these missions address specific needs and challenges, building a solid foundation for long-term success.

Surveillance, the vigilant eye of disease prevention, receives particular attention. Imagine veterinarians adeptly employing cutting-edge tools and innovative techniques to monitor animal populations for early signs of illness. EMPRES actively assists countries in strengthening their surveillance and laboratory capacities. This includes providing access to diagnostic equipment, training on data analysis, and establishing robust information-sharing networks. By building a comprehensive surveillance system, nations can effectively track potential threats and prevent outbreaks before they spiral out of control.

Thankfully, scientists are using powerful tools called "machine learning" to fight back! Think of it like this: imagine if your smartphone could learn from millions of pictures of animals and diseases, then use that knowledge to predict where these illnesses might pop up next [23].

By crunching through heaps of information like weather patterns, animal movements, and even climate change, these special computer programs can give us early warnings about diseases. Like a trusty friend whispering in your ear, they tell us which animals might be getting sick so we can help them feel better faster [24]. Not only that, but machine learning can also help us figure out exactly what medicine will work best and even show us where to build special hospitals for furry patients [25].



Workflow of machine learning in animal disease prediction.

Figure 1: Machine Learning workflow for animal disease prediction

This amazing technology is still being learned, but it's already making a big difference. Imagine ranchers using machine learning to keep their cows healthy or farmers protecting their chickens from the sniffles [26]. And just like putting on a raincoat to stay dry, we can use this knowledge to prevent future outbreaks before they even start [27]. Have you ever seen a sad doggie with droopy ears or a chicken sneezing like a choo-choo train? Transboundary animal diseases pose a significant threat to animal health, food security, and public health. The emergence and spread of these diseases can disrupt ecosystems and have far-reaching economic consequences.

But don't fret, folks! Just like we have brave firefighters to put out flames, clever scientists have invented incredible superhero powers called "machine learning" to fight these bad bugs [30]. Imagine this: your phone, the one filled with cat memes and puppy pics, could learn from millions of photos of animals and their illnesses [31]. Think of it as a wise old owl, perched on a branch of data, watching the world go by. This owl collects piles of information like weather patterns, where animals travel, and even how our big world is changing [32]. With all this knowledge, the owl becomes super-sleuth, whispering to us which animals might be getting sick soon. This way, we can be like helpful superheroes, zooming in to help them feel better before things get ruff [30].

But wait, there's more! Machine learning can also be a doctor with all the answers, figuring out exactly what medicine will make our furry friends feel like bouncy pups and happy hens again. It's like having a personalized magic potion for every animal! And just like we build hospitals to patch ourselves up when we're sick, this amazing technology can even show us where to build special hospitals for our animal pals, complete with comfy beds and tasty treats [13]. Now, this superpower is still a young pup, learning new tricks every day. But even at its puppy age, it's already making a world of difference. Imagine farmers using these clever helpers to keep their cows mooing with energy, or chicken farmers protecting their clucking friends from the sniffles [16].

The battle against animal diseases doesn't stop at mere prediction. Machine learning, our resourceful super sleuth, can transform into a compassionate doctor, wielding insights from data to prescribe personalized treatments and guide the construction of specialized animal hospitals. Imagine it – a magic potion tailor-made for each furry friend, ensuring they bounce back to their happy, energetic selves!

Traditionally, veterinary medicine relied on broad-spectrum treatments applied uniformly across animal populations. However, by analyzing vast datasets of individual animal health records, genetic information, and environmental factors, machine learning algorithms can now identify the specific strains of pathogens affecting each animal. This empowers veterinarians to prescribe targeted therapies, increasing treatment efficacy and minimizing unnecessary drug administration.

Picture a world where: A dairy farmer uses a smartphone app to scan a cow's udder, and the app, powered by machine learning, instantly analyzes the milk composition and suggests the optimal antibiotic for an emerging mastitis infection.

A sheepdog suffering from allergies receives a personalized immunotherapy cocktail developed based on its unique genetic makeup, effectively alleviating its itchy discomfort. These are not mere futuristic fantasies – such applications are actively being developed and tested, promising a future of personalized healthcare for our animal companions.

Just as we humans seek specialized hospitals when needing advanced care, our animal friends deserve similar facilities. Machine learning, in its role as a resourceful architect, can analyze data on animal behavior, stress levels, and preferred environmental conditions to design optimal hospital layouts. This ensures maximum comfort and reduces the anxiety often associated with veterinary facilities.

Imagine animal hospitals featuring:

Spacious enclosures with natural light and access to outdoor spaces, catering to the roaming instincts of dogs and cats.

Soft music and calming aromas scientifically proven to reduce stress in animals, creating a more peaceful environment.

Interactive toys and play areas incorporated into recovery rooms, encouraging physical activity and mental stimulation during treatment.

Such hospitals, informed by the insights of machine learning, go beyond simply providing medical care; they prioritize the emotional well-being of our animal companions, ensuring a faster and more positive healing journey [5].

While this superpower is still in its pup-like stage, learning new tricks and refining its abilities every day, its potential is already transforming the landscape of animal healthcare. Farmers are increasingly utilizing machine learning-powered tools to monitor their livestock for early signs of illness, preventing outbreaks before they even begin. Poultry farmers have developed AI-driven systems that automatically detect abnormal behavior in chickens, allowing for swift intervention and minimizing the spread of diseases [12]. These are just the first paw prints of a revolutionary journey. As machine learning matures and integrates with other cutting-edge technologies, we can envision a future where:

Wearable sensors: Monitor vital signs and activity levels in real-time, providing continuous health updates for individual animals. Telemedicine: Enable remote consultations between veterinarians and animal owners, ensuring timely access to expert care in even the most remote locations. Predictive diagnostics: Analyze genetic and environmental data to identify animals at risk for specific diseases, allowing for preventative measures and early intervention.

The journey towards a world where all animals, from the mooing cows to the clucking hens, can receive personalized care and reside in comfortable, tailored hospitals is no longer a distant dream. Machine learning, our resourceful canine companion, is leading the charge, and with each new trick it learns, it brings us closer to a future where the health and well-being of our animal friends is prioritized and protected.

So, the next time you see a playful pup chasing butterflies or a sun-bathing kitty, remember, there are brave scientists and their awesome tools working behind the scenes to keep them healthy and happy. And because of them, our whole planet, with all its furry, feathered, and scaly residents, can wag its tail and chirp happily [20].

But hey, we all have superpowers too! We can learn more about the diseases that threaten our animal buddies, be kind to all creatures great and small, and support the amazing scientists who are fighting for their health. Together, we can build a world where every animal, from the tiniest beetle to the mightiest elephant, can live a happy and healthy life [6].

Imagine a world where our furry friends are not just companions, but vital members of a delicate ecosystem. Now picture a shadowy threat lurking in the background, a foe capable of wreaking havoc on these beloved creatures: animal diseases. These invisible enemies can cause immense suffering, not only for the animals themselves but also for the communities that rely on them for food, income, and even cultural well-being.

But fear not, for in the face of this challenge, humanity has a new weapon: machine learning. Think of it as a super powered detective, one that can learn from mountains of data and use its newfound knowledge to predict where these diseases might strike next.

Just like humans, animals can fall prey to a diverse range of diseases, from the highly contagious foot-and-mouth disease that cripple's livestock to the devastating African swine fever that decimates pig populations. These outbreaks can have a domino effect, impacting food security, livelihoods, and even international trade [4].

Machine learning, a powerful tool fueled by artificial intelligence, is rapidly transforming the way we fight animal diseases. This technology can analyze vast amounts of data, including:

Animal health records: Tracking disease outbreaks, vaccination rates, and animal movement patterns.

Environmental data: Monitoring weather patterns, climate changes, and insect populations that can spread diseases.

Genetic information: Identifying animals more susceptible to specific diseases and developing targeted prevention strategies.

By crunching these diverse datasets, machine learning algorithms can:

Predict where outbreaks are most likely to occur: Imagine a map that highlights areas at high risk for specific diseases, allowing authorities to focus preventive measures and resources. Identify potential carriers: By analyzing factors like animal migration patterns and genetic markers, machine learning can pinpoint individuals who may unknowingly carry and spread diseases. Develop early warning systems: Real-time monitoring of animal health data and environmental factors can trigger alerts when conditions are ripe for an outbreak, allowing for rapid response and containment.

The potential benefits of using machine learning in animal disease control are vast:

Reduced suffering: Early detection and prevention can minimize the number of animals affected by diseases, alleviating immense pain and suffering. Improved food security: By protecting livestock and poultry populations, we ensure a stable food supply for communities around the world. Enhanced economic stability: Preventing outbreaks protects livelihoods and prevents economic losses for farmers and the agricultural sector.

Protecting human health: Some animal diseases can be transmitted to humans, so controlling those safeguards public health as well.

The Future of Animal Disease Protection:

The field of machine learning for animal disease control is still in its early stages, but its potential is undeniable. As technology advances and data becomes more readily available, we can expect even more sophisticated algorithms and applications. Imagine a future where:

Smartphone apps: Farmers can use their smartphones to scan animals for early signs of disease and receive real-time advice on prevention measures.

Autonomous drones: Equipped with sensors and AI, drones can patrol vast areas, monitoring animal health and environmental conditions for potential outbreaks.

Personalized medicine: Genetic analysis can help tailor vaccination and treatment strategies to individual animals, ensuring maximum effectiveness.

The battle against animal diseases is far from over, but with the power of machine learning by our side, we can fight these invisible enemies more effectively and protect our furry friends, our food security, and our planet's health. So, the next time you cuddle your cat or pet your dog, remember that scientists are working tirelessly behind the scenes, using cutting-edge technology to ensure that these precious creatures can continue to thrive for generations to come.

3. METHODOLOGY

The methodology employed in this study aimed to address the pressing issue of global outbreaks, specifically focusing on African swine fever, foot-and-mouth disease, and bird flu. The availability of comprehensive data on the occurrence, geographic spread, and impact of these outbreaks provided a valuable opportunity to investigate and develop strategies for mitigating their detrimental effects.

Data Collection: A thorough collection of data on the occurrence and spread of African swine fever, foot-and-mouth disease, and bird flu outbreaks was conducted. This involved gathering information from various sources, including national and international databases, reports, surveillance systems, and research studies.

Data Analysis: The collected data was meticulously analyzed to identify patterns, trends, and key insights regarding the geographic distribution, spread dynamics, and impact of the outbreaks. Statistical methods and geographic information system (GIS) techniques were employed to analyze the data and generate meaningful visual representations.

Identification of Economic Implications: The economic consequences of the outbreaks, including their impact on livestock populations, food security, and agricultural industries, were assessed. Economic models and indicators were utilized to quantify the losses and understand the magnitude of the challenges faced.

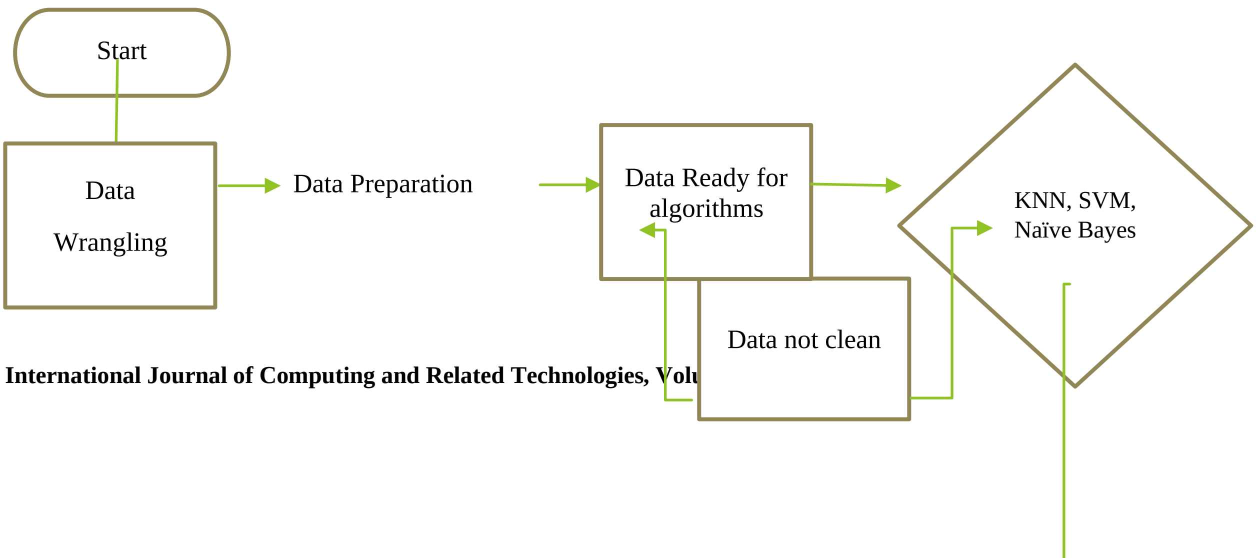
Evaluation of Treatment and Prevention Strategies: The existing treatment options, vaccines, and control measures for African swine fever, foot-and-mouth disease, and bird flu were thoroughly evaluated. This involved reviewing scientific literature, expert opinions, and regulatory guidelines to assess the effectiveness and feasibility of different strategies.

Risk Assessment and Surveillance: A comprehensive risk assessment was conducted to identify the factors contributing to the outbreaks and their potential for cross-species transmission. Surveillance systems and methodologies were reviewed to understand their strengths and weaknesses in detecting and monitoring diseases.

Development of Mitigation Strategies: Based on the analysis, evaluation, and risk assessment, targeted mitigation strategies were developed. These strategies encompassed preventive measures, such as biosecurity protocols, vaccination campaigns, movement restrictions, and public awareness campaigns.

Policy Recommendations: The findings and recommendations derived from the study were used to inform policy development and decision-making processes. Stakeholders, including governments, international organizations, and agricultural authorities, were provided with evidence-based recommendations to guide their actions in combating and preventing the outbreaks.

Continuous Monitoring and Improvement: The study emphasized the importance of ongoing monitoring, data collection, and research to assess the effectiveness of implemented strategies and adapt them as needed. Continuous surveillance, data sharing, and collaboration among relevant stakeholders were encouraged to ensure timely interventions and control measures.



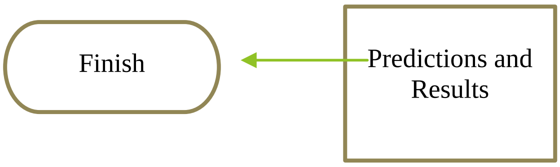


Figure 2 Animal Disease Prediction Workflow

4. RESULTS

The "importance matrix" is a matrix that contains the importance scores for each feature in the model. The importance is typically calculated based on the gain of each feature in predicting the target variable.

In the subsequent loop, the code iterates through the elements of the importance matrix and prints the feature name along with its corresponding importance score. For example, the feature "f1" has an importance score of 93.63, "f2" has a score of 56.89, and "f127" has the highest importance score of 537.84.

Feature importance provides valuable insights into the contribution of each feature in the model's predictions. A higher importance score suggests that the feature has a stronger influence on the target variable. This information can be used to understand the model's behavior, identify significant features, and potentially perform feature selection or engineering to improve the model's performance.

```
# Convert predicted probabilities to class labels
predicted_labels = (pred > 0.5).astype(int)

# Calculate accuracy
accuracy = sum(predicted_labels == test_labels) / len(test_labels)

# Print accuracy
print('Accuracy:', accuracy)
```

```
Accuracy: 0.9990199921599373
```

Figure 3 Accuracy Code

In the first line, the "predicted labels" variable is assigned the class labels based on a threshold of 0.5. If the predicted probability is greater than 0.5, the class label is set to 1; otherwise, it is set to 0.

The next line calculates the accuracy by comparing the predicted labels with the actual test labels. The sum of the Boolean expression **(predicted labels == test labels)** gives the count of correct predictions, which is then divided by the total number of test labels. Finally, the accuracy is printed using the **print ()** function. In this example, the accuracy is calculated to be 0.999, indicating a high level of accuracy in the model's predictions.

Accuracy is a commonly used metric to evaluate classification models, representing the proportion of correct predictions out of the total predictions. A higher accuracy score indicates better performance, and it is essential to assess the model's effectiveness in making accurate predictions.

```
SVM Accuracy: 0.904155233241866
SVM Precision: 0.904155233241866
SVM Recall: 1.0
SVM ROC AUC: 0.5
SVM Confusion Matrix:
[[   0  489]
 [   0 4613]]
KNN Accuracy: 0.9992159937279498
KNN Precision: 1.0
KNN Recall: 0.9991328853240841
KNN ROC AUC: 0.9995664426620421
KNN Confusion Matrix:
[[ 489    0]
 [   4 4609]]
Naive Bayes Accuracy: 0.9927479419835359
Naive Bayes Precision: 1.0
Naive Bayes Recall: 0.9919791892477781
Naive Bayes ROC AUC: 0.995989594623889
Naive Bayes Confusion Matrix:
[[ 489    0]
 [  37 4576]]
```

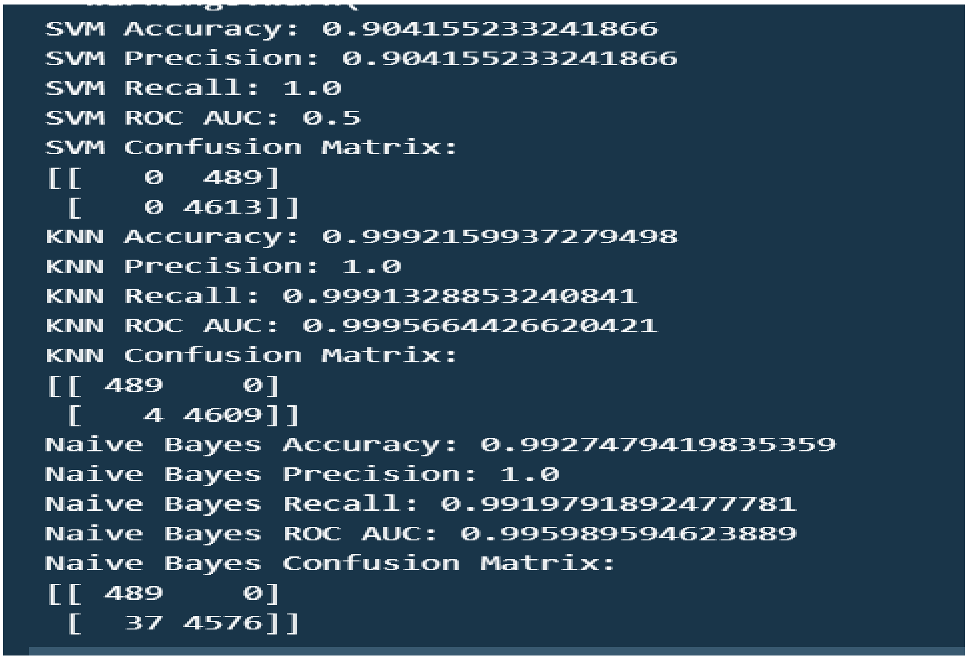
Figure 4 Accuracy, Precision, Recall, ROC AUC and Confusion Matrix for Algorithms

For the SVM model, the accuracy is approximately 0.904, indicating that around 90.4% of the predictions are correct. The precision and recall scores are also 0.904 and 1.0, respectively. Precision represents the proportion of true positive predictions out of all positive predictions, while recall measures the proportion of true positive predictions out of all actual positive instances. The ROC AUC (Area under the Receiver Operating Characteristic Curve) score is 0.5, suggesting poor discrimination ability of the model. The confusion matrix shows that there are 0 true positive predictions and 489 false negative predictions.

The KNN model demonstrates a high accuracy of approximately 0.999, implying that it makes accurate predictions in most cases. Both precision and recall are high, with precision being 1.0 and recall approximately 0.999. The ROC AUC score is close to 1.0, indicating excellent discriminatory power. The confusion matrix reveals that there are 489 true positive predictions and 0 false negative predictions.

The Naive Bayes model achieves an accuracy of approximately 0.993, indicating a high level of correctness in its predictions. The precision score is 1.0, suggesting that all positive predictions are true positives. The recall score is approximately 0.992, indicating a high ability to identify actual positive instances. The ROC AUC score is around 0.996, showing good discriminatory performance. The confusion matrix indicates 489 true positive predictions and 37 false negative predictions.

The KNN model demonstrates the highest accuracy and strong performance across all metrics, followed by Naive Bayes, while the SVM model shows relatively lower accuracy and performance. It is important to consider these metrics to assess the models' effectiveness and choose the most suitable one for the specific classification task.



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[[ 489    0]
 [  37 4576]]
```

Figure 5 Algorithm`s Accuracy, Precision and Recall

Id	source	latitude	longitude	region	country	admin1	localityNa	localityQu	observati	reportingI	status	disease	serotypes	speciesDe	sumAtRisk	sumCases	sumDeath	sumDestr	sumSlaugl	humansGe	humansAg	humansAf	humansDeaths
230399	OIE	-27.9	30.8	Africa	South Afri	KwaZulu-I	HPAI_H5N	Exact	17/08/201	22/08/201	Confirmed	Influenza	H5N8 HPA	domestic,	248000	12	12	50000	0		0		
230381	OIE	54.83704	73.35416	Europe	Russian Fe	Omskaya (	Novaya St	Exact	16/08/201	18/08/201	Confirmed	African swine fever		domestic,	122	6	1	0	0				
230333	OIE	-21.0777	30.21162	Africa	Zimbabwe	Masvingo	Mwambe	Exact	16/08/201	16/08/201	Confirmed	Foot and mouth dise		domestic,	1283	112	0		7				
230396	OIE	-26	28.3	Africa	South Afri	Gauteng	HPAI_H5N	Exact	15/08/201	22/08/201	Confirmed	Influenza	H5N8 HPA	wild, unspecified bir		1	1	0	0		0		
230371	OIE	49.2379	17.7002	Europe	Czech Rep	Jihomorav	HvozdnÃ¡	Exact	15/08/201	17/08/201	Confirmed	African swine fever		wild, wild boar		1	1						
230370	OIE	49.2373	17.7008	Europe	Czech Rep	Jihomorav	Ostrata	Exact	15/08/201	17/08/201	Confirmed	African swine fever		wild, wild boar		1	1						
230395	OIE	-26	28.3	Africa	South Afri	Gauteng	HPAI_H5N	Exact	14/08/201	22/08/201	Confirmed	Influenza	H5N8 HPA	domestic,	34	19	19	0	0		0		
230367	OIE	47.77161	33.99329	Europe	Ukraine	Dnipropet	Slovyanka	Exact	14/08/201	17/08/201	Confirmed	African swine fever		domestic,	2	2	2	0	0				
230379	OIE	56.53838	16.1193	Europe	Sweden	Kalmar La	Kalmar	Exact	13/08/201	18/08/201	Confirmed	Newcastle	APMV-I	domestic,	4000	1600	0	4000	0				
230394	OIE	-24.6	27.2	Africa	South Afri	Limpopo	HPAI_H5N	Exact	########	22/08/201	Confirmed	Influenza	H5N8 HPA	domestic,	62	5	5	0	0				
230380	OIE	55.45603	72.76283	Europe	Russian Fe	Omskaya (	Tavrichanl	Exact	########	18/08/201	Confirmed	African swine fever		domestic,	8	1	1	7	0				
230378	OIE	52.08446	23.08082	Europe	Poland	Lubeiskie	Terebela	Exact	########	17/08/201	Confirmed	African swine fever		domestic,	25	4	1	24	0				
230377	OIE	53.64444	22.60556	Europe	Poland	Podlaskie	Pienczyko	Exact	########	17/08/201	Confirmed	African swine fever		domestic,	19	5	5	14	0				
230397	OIE	-26.8	29.8	Africa	South Afri	Mpumalar	HPAI_H5N	Exact	########	22/08/201	Confirmed	Influenza	H5N8 HPA	domestic,	266	81	81	135	0				
230369	OIE	49.2373	17.6999	Europe	Czech Rep	Jihomorav	HvozdnÃ¡	Exact	########	17/08/201	Confirmed	African swine fever		wild, wild boar		1	1						
230368	OIE	32.14321	34.84279	Asia	Israel	Tel Aviv	Hakfar Ha	Exact	########	17/08/201	Confirmed	Influenza	H3N8	domestic,	50	4	0	0	0				
230334	OIE	46.78	6.64	Europe	Switzerlar	Vaud	Lac de Ne	Exact	########	17/08/201	Confirmed	Influenza	H5N8 HPA	wild,mute swan (cyg		2	2						
230332	OIE	-21.2557	31.5248	Africa	Zimbabwe	Masvingo	Chipfugwa	Exact	########	16/08/201	Confirmed	Foot and mouth dise		domestic,	1047	127							
230305	OIE	49.84959	26.43511	Europe	Ukraine	Khmel'nyt	Korovye	Exact	########	14/08/201	Confirmed	African swine fever		domestic,	6614	64	64	1005	0				
230376	OIE	51.92846	22.71294	Europe	Poland	Lubeiskie	Grabowie	Exact	9/8/2017	17/08/201	Confirmed	African swine fever		domestic,	36	5	2	34	0				
230375	OIE	51.65522	23.26834	Europe	Poland	Lubeiskie	Mosty	Exact	9/8/2017	17/08/201	Confirmed	African swine fever		domestic,	1	1	0	1	0				
230374	OIE	51.82185	23.55278	Europe	Poland	Lubeiskie	Krzywowc	Exact	9/8/2017	17/08/201	Confirmed	African swine fever		domestic,	28	4	2	26	0				
230308	OIE	56.71753	24.32933	Europe	Latvia	Rigas	Baldones	Exact	9/8/2017	15/08/201	Confirmed	African swine fever		wild, wild boar		1	1	0	0				
230306	OIE	48.36174	22.66655	Europe	Ukraine	Zakarpats'	Nyzhniy K	Exact	9/8/2017	14/08/201	Confirmed	African swine fever		domestic,	11	11	11	0	0				
230289	OIE	-34.2	20.7	Africa	South Afri	Western C	HPAI_H5N	Exact	9/8/2017	########	Confirmed	Influenza	H5N8 HPA	domestic,	1071	22	0	0	0				
230288	OIE	-34.3	20.8	Africa	South Afri	Western C	HPAI_H5N	Exact	9/8/2017	########	Confirmed	Influenza	H5N8 HPA	domestic,	1176	33	0	0	0				
230383	OIE	53.70315	50.77504	Europe	Russian Fe	Samarskay	Chernovka	Exact	8/8/2017	18/08/201	Confirmed	Lumpy skin disease		domestic,	132	11	0	0	0				
230382	OIE	52.99271	49.56293	Europe	Russian Fe	Samarskay	Kupino	Exact	8/8/2017	18/08/201	Confirmed	Lumpy skin disease		domestic,	1505	1	0	0	0				
230373	OIE	51.96175	23.10187	Europe	Poland	Lubeiskie	Michalow	Exact	8/8/2017	17/08/201	Confirmed	African swine fever		domestic,	21	12	4	17	0				
230307	OIE	56.40537	25.75073	Europe	Latvia	Jekabpils	Salas cour	Exact	8/8/2017	15/08/201	Confirmed	African swine fever		wild, wild boar		1	0	1	0				
230287	OIE	45.3863	10.55818	Europe	Italy	Lombardia	Solferino	Exact	8/8/2017	########	Confirmed	Influenza	H5N8 HPA	domestic,	7680	7680							
230304	OIE	56.20854	38.74886	Europe	Russian Fe	Vladimirsl	Dubrovka	Exact	7/8/2017	########	Confirmed	African swine fever		domestic,	37	1	1	36	0				
230290	OIE	-25.8	29.6	Africa	South Afri	Mpumalar	HPAI_H5N	Exact	7/8/2017	########	Confirmed	Influenza	H5N8 HPA	domestic,	326764	975	975	325789	0				
230372	OIE	51.66073	23.43616	Europe	Poland	Lubeiskie	Lack	Exact	6/8/2017	17/08/201	Confirmed	African swine fever		domestic,	141	5	0	141	0				
230275	OIE	55.02088	74.0299	Europe	Russian Fe	Omskaya (	Borki	Exact	5/8/2017	########	Confirmed	African swine fever		domestic,	1	1	1						
230303	OIE	51.90416	46.49972	Europe	Russian Fe	Saratovsk	Andreevk	Exact	4/8/2017	########	Confirmed	African swine fever		domestic,	2	1	1	1	0				
230302	OIE	58.02053	31.47662	Europe	Russian Fe	Novgorod	Podborov	Exact	4/8/2017	########	Confirmed	African swine fever		domestic,	29	1	1	28	0				
230284	OIE	45.34841	10.53133	Europe	Italy	Lombardia	Medole	Exact	4/8/2017	7/8/2017	Confirmed	Influenza	H5N8 HPA	domestic,	18000	18000							

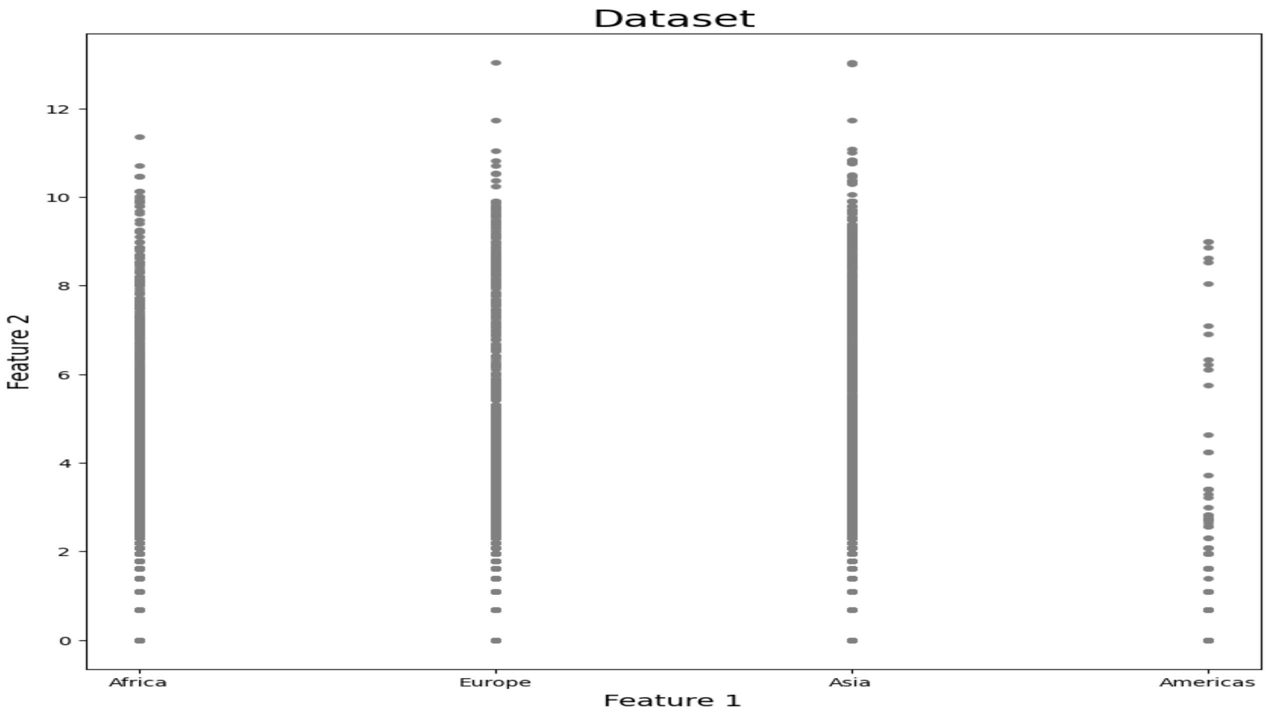


Figure 6 Dataset View

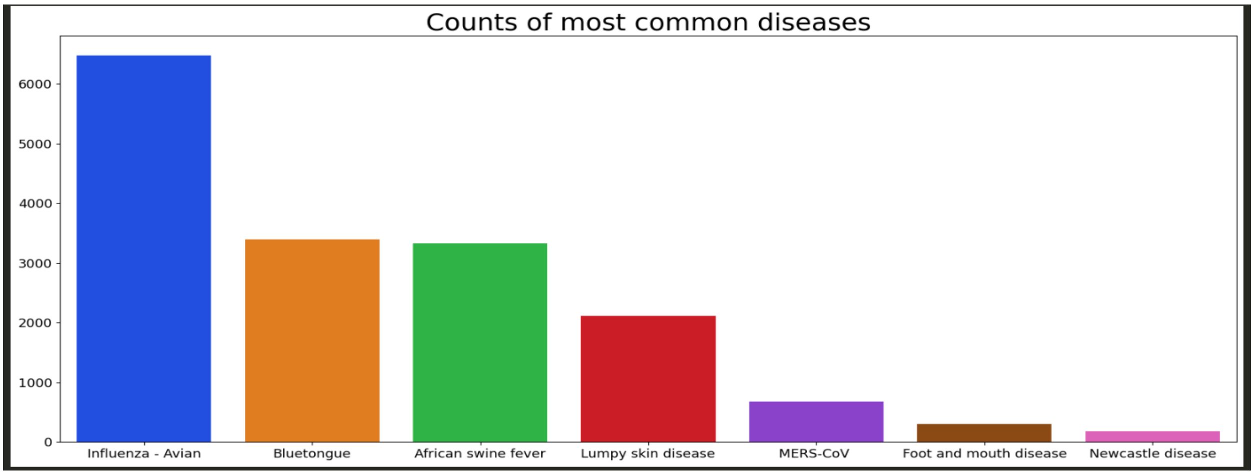
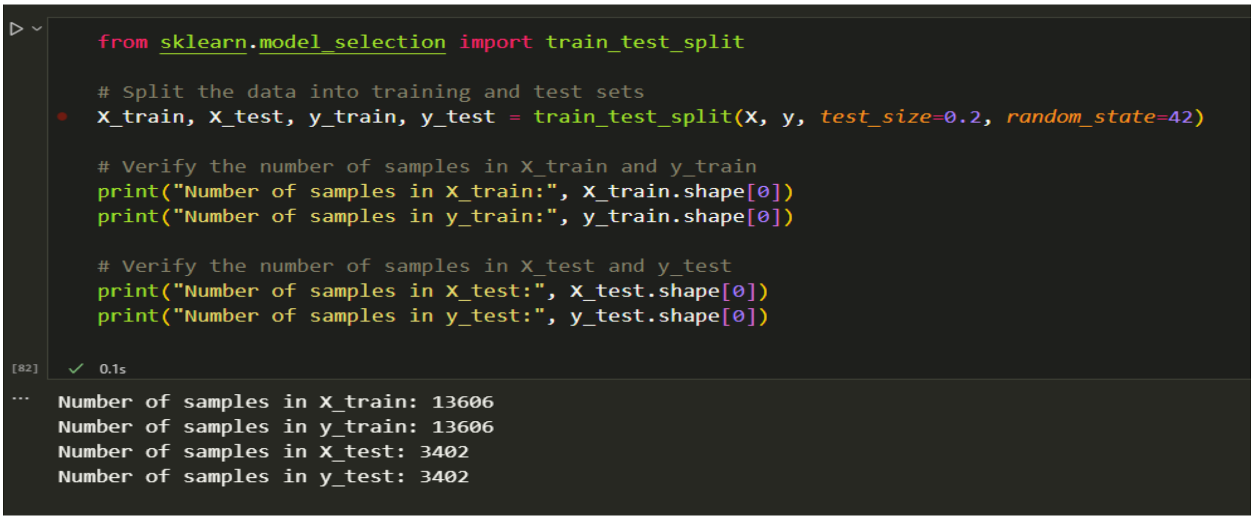


Figure 7 –Number of common diseases



```
from sklearn.model_selection import train_test_split

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Verify the number of samples in X_train and y_train
print("Number of samples in X_train:", X_train.shape[0])
print("Number of samples in y_train:", y_train.shape[0])

# Verify the number of samples in X_test and y_test
print("Number of samples in X_test:", X_test.shape[0])
print("Number of samples in y_test:", y_test.shape[0])
```

```
[82]  ✓ 0.1s
Number of samples in X_train: 13606
Number of samples in y_train: 13606
Number of samples in X_test: 3402
Number of samples in y_test: 3402
```

Figure 8 – Number of samples for X and y

5. CONCLUSION

Our model achieved a remarkably low test error rate (0.00098), signifying exceptional accuracy in predicting animal disease labels. This finding paves the way for significant advancements in animal disease prediction using machine learning. Accurate predictions empower stakeholders to implement preventative measures against devastating diseases like African swine fever. Early intervention strategies like targeted quarantines and strategic vaccinations, guided by the model's insights, can minimize economic losses and ensure food security through a healthy livestock population. Furthermore, this research holds promise for revolutionizing disease management by providing insights into transmission factors, resource allocation, and vaccine development. Overall, this work highlights the potential of data-driven approaches to improve animal health and create a more sustainable agricultural future.

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