Kudakwashe Chakanyuka - Final Project Report

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Cat Disease Detector

A Multimodal Machine Learning System for Feline Health Diagnosis

1 Introduction and Problem Setup

The Cat Disease Detector addresses the pressing challenge of early feline disease detection, a critical issue stemming from cats' natural tendency to conceal symptoms, which often delays diagnosis and treatment until conditions become severe, compounded by geographic, financial, or logistical barriers that limit access to veterinary care, particularly in rural or underserved areas. To bridge this gap, the system offers a user-friendly diagnostic tool that employs machine learning to analyze multimodal inputs, integrating textual symptom descriptions, such as lethargy, vomiting, and diarrhea, with visual data from images of affected cat body parts, to predict one of ten common feline diseases, including feline leukemia, dermatitis, and panleukopenia. Structured as a two-stage classification task, the system first performs a binary cat versus non-cat classification to ensure input images depict felines, filtering out irrelevant subjects like dogs or birds for diagnostic accuracy, before proceeding to a multi-class disease prediction that leverages visual cues, textual symptoms, or a combination of both, utilizing complementary information to enhance reliability and support timely veterinary intervention.

2 Literature Review

The Cat Disease Detector is designed to tackle the significant challenge of early feline disease detection, addressing the difficulty posed by cats' natural tendency to conceal symptoms, which often delays diagnosis and treatment. By developing a multimodal machine learning system, the project integrates textual symptom descriptions, such as vomiting, lethargy, and diarrhea, with visual data from images of affected cat body parts to predict one of ten common feline diseases, including feline leukemia, dermatitis, and panleukopenia. The problem is structured as a two-stage classification task: first, a binary cat versus non-cat classification ensures that input images depict felines, filtering out irrelevant subjects like dogs or birds to maintain diagnostic accuracy; second, a multi-class disease prediction leverages visual cues, textual symptoms, or both to identify the specific disease, utilizing complementary information from these modalities to enhance reliability. This approach aims to bridge gaps in veterinary care, particularly in rural or underserved areas, by providing a user-friendly tool that facilitates timely intervention, reducing health complications and veterinary costs while improving outcomes for feline health.

The machine learning techniques employed in the Cat Disease Detector are grounded in statistical learning theory, which seeks to minimize empirical risk, defined as $R(f) = E[L(y, f(x))]$, where L is the loss function, y is the true label, and $f(x)$ is the model's prediction, approximated through empirical risk minimization, $\hat{R}(f) = \frac{1}{n}\sum_{i=1}^{n} L(y_i, f(x_i))$, with L2 regularization to balance bias and variance. Cross-entropy loss, $L = -\sum_{k=1}^{K} y_k \log(\hat{y}_k)$, optimizes both the binary cat versus non-cat task and the multi-class disease prediction, using the Adam optimizer to efficiently navigate high-dimensional loss landscapes. Convolutional neural networks (CNNs) process images, applying filters to detect patterns like edges, with outputs computed as $z_{i,j,k} = \sum_m \sum_n \sum_c w_{m,n,c,k} x_{i+m,j+n,c} + b_k$, followed by ReLU activation, max-pooling, and dropout to ensure robustness. For sequential symptom data, recurrent neural networks (RNNs) with Long Short-Term Memory (LSTM) units process 300-dimensional GloVe embeddings to capture temporal dependencies, estimating $P(y|x_1, \ldots, x_T)$ and overcoming vanishing gradient issues. The softmax function, $\hat{y}_k = \frac{\exp(z_k)}{\sum_{j=1}^{K} \exp(z_j)}$, generates probabilities for disease prediction, while the sigmoid function, $\hat{y} = \frac{1}{1+\exp(-z)}$, supports binary classification. Training involves 20 epochs for the cat versus non-cat CNN and 25–30 epochs for disease prediction models, with early stopping to prevent overfitting, ensuring models learn robust patterns from noisy veterinary datasets.

In the veterinary domain, machine learning is transforming diagnostics by moving beyond rule-based systems to data-driven models that leverage complex datasets, yet it faces challenges such as class imbalance for rare diseases like feline leukemia, non-specific symptoms like lethargy or vomiting, and smaller, noisier datasets compared to human medical data. The Cat Disease Detector mitigates these through stratified sampling, probabilistic models using softmax and sigmoid functions, and extensive data augmentation, with training epochs carefully tuned to avoid overfitting. Although the targeted feline diseases, such as panleukopenia and mange, are not directly zoonotic, their untreated progression can lead to secondary infections like Bartonella, transmissible to humans via scratches or bites, increasing environmental contamination risks. By enabling early detection, the system reduces disease progression, aligning with the One Health framework that emphasizes interconnected human, animal, and environmental health. The project's techniques, including multimodal data integration and probabilistic outputs, are adaptable to directly zoonotic diseases like rabies or toxoplasmosis, offering potential for broader public health applications. By proactively addressing feline health, the Cat Disease Detector contributes to preventing disease cascades that could impact human populations, particularly in households with close human-cat interactions, while setting a foundation for advanced veterinary diagnostics.

3 Data Exploration

To construct a robust machine learning system for the Cat Disease Detector, a thorough exploration of three raw datasets was undertaken to assess their structure, quality, and suitability for the classification tasks of cat versus non-cat identification and feline disease prediction. The first dataset, sourced from Kaggle's publicly available "Cat Breeds and Images" collection, comprises 10,000 images of healthy cats spanning various breeds, capturing a diverse array of appearances, including different fur colors, patterns, and facial structures. These images, characterized by varying lighting conditions, backgrounds, and poses, reflect the real-world variability essential for training a generalizable model. Visual inspection of sample images confirmed the presence of feline-specific features, such as pointed ears, whiskers, and slit-like pupils, which are critical for distinguishing healthy cats from both unhealthy cats and non-cat animals. Analysis of pixel intensity histograms revealed a broad range of color distributions, with a mean of 0.45 and a standard deviation of 0.22, indicating diverse image characteristics. Approximately 5% of the images were identified as noisy, exhibiting blurriness or low resolution, necessitating preprocessing to ensure model robustness. The dataset's key features, including fur patterns like tabby stripes or solid colors, facial structures such as ear shapes, and body proportions, provide essential cues for convolutional neural network (CNN) training, enabling the model to learn distinctive traits of healthy felines.

The second dataset, aggregated from veterinary databases, the UCI Machine Learning Repository, and the Petfinder API, focuses on unhealthy cats, encompassing 10,000 images of cats exhibiting symptoms of ten diseases, such as dermatitis, conjunctivitis, and feline leukemia, paired with 1,000 textual symptom descriptions per disease compiled from veterinary manuals and clinic websites. Visualization of disease-specific images revealed characteristic visual markers, such as redness associated with dermatitis or nasal discharge indicative of calicivirus, which are vital for accurate disease prediction. Term Frequency-Inverse Document Frequency (TF-IDF) analysis of the symptom descriptions identified frequent terms, with "vomiting" appearing in 80% of diseases, "lethargy" in 70%, and "diarrhea" in 50%, highlighting the challenge of symptom overlap across conditions. A notable class imbalance was observed, with dermatitis represented by 1,500 images and feline leukemia by only 600, posing a challenge for balanced training and requiring careful data handling to ensure equitable model performance. The dataset's localized visual symptoms, such as skin lesions and eye abnormalities, alongside symptom co-occurrences like vomiting and lethargy, underscore the need for both CNNs and recurrent neural networks (RNNs) to capture complementary visual and textual information, enhancing the system's diagnostic capabilities.

The third dataset, drawn from UCI's "Animal Image Dataset" and Kaggle's "Pets and Animals" collections, includes 10,000 images of non-cat animals, such as dogs, birds, rabbits, and reptiles, designed to train the model to reject non-feline inputs. Visual analysis confirmed structural differences, such as dog snouts versus cat whiskers or bird feathers versus cat fur, which are critical for negative classification. Texture analysis using Gabor filters further distinguished fur from non-fur textures, aiding in feature differentiation and ensuring the model learns to identify the absence of feline-specific traits, such as whiskers or ear shapes. The dataset's diversity strengthens the CNN's ability to robustly filter out irrelevant inputs, a crucial step in the classification pipeline. To prepare these datasets for machine learning, extensive preprocessing was performed. All images were resized to a uniform 224×224 pixel resolution to standardize input dimensions for the CNN and normalized to the $[0, 1]$ range to stabilize training. Data augmentation techniques, including random rotations up to 20 degrees, horizontal flipping, and brightness adjustments, were applied to enhance dataset diversity and improve model robustness to real-world variations. Textual symptom descriptions were tokenized using the Natural Language Toolkit (NLTK), with stopwords like "the" and "and" removed to reduce noise, and words were stemmed to normalize variations, such as "vomiting" and "vomit." Each symptom sequence was converted to 300-dimensional GloVe embeddings to capture semantic relationships, facilitating RNN processing. The datasets were split into 80% training, 10% validation, and 10% testing sets, with stratified sampling applied to the unhealthy cat dataset to address class imbalance, ensuring proportional representation of each disease across all splits. This comprehensive data exploration and preprocessing laid a solid foundation for the subsequent development and training of the Cat Disease Detector's machine learning models.

4 Methodology

The Cat Disease Detector employs a sophisticated, two-stage machine learning pipeline designed to address the challenge of early feline disease detection through a multimodal approach, integrating both visual and textual data. This system leverages convolutional neural networks (CNNs) for image-based analysis and recurrent neural networks (RNNs) with Long Short-Term Memory (LSTM) units for symptom-based processing, culminating in a hybrid model that combines both modalities to enhance diagnostic accuracy. Implemented using TensorFlow, the methodology is structured to handle the complexity of classifying cats versus non-cat animals and predicting one of ten common feline diseases, such as dermatitis, conjunctivitis, and feline leukemia, based on complementary visual and textual cues.

The first stage of the pipeline focuses on cat versus non-cat classification, a binary task critical for ensuring that subsequent disease predictions are applied only to feline subjects. A CNN with three convolutional layers, comprising 32, 64, and 128 filters respectively, processes input images resized to a uniform 224×224 pixel resolution. Each layer employs 3×3 filters with ReLU activation to capture local patterns such as edges and textures, followed by max-pooling (2×2) to reduce spatial dimensions and enhance translation invariance. A fully connected layer with sigmoid activation produces a probability score, where a threshold of 0.5 determines whether the input is a cat. The model is trained using binary cross-entropy loss, optimized with the Adam optimizer at a learning rate of 0.001, over 20 epochs. Early stopping is implemented, halting training if validation loss does not improve for five consecutive epochs, ensuring convergence without overfitting. This approach leverages the statistical foundation of empirical risk minimization, approximating the expected loss over the dataset to achieve robust generalization.

The second stage, disease prediction, is more complex, involving three distinct models: an image-based CNN, a symptom-based RNN with LSTM units, and a combined multimodal model. For image-based disease prediction, a deeper CNN with 256 filters in its final convolutional layer processes images of unhealthy cats exhibiting visible symptoms, such as lesions or eye discharge. Dropout with a probability of 0.5 is applied to mitigate overfitting, particularly given the variability in veterinary imaging data. A softmax output layer transforms logits into probabilities for ten diseases, facilitating multi-class classification. The model is trained for 30 epochs using categorical cross-entropy loss and Adam optimization, with early stopping to balance convergence and generalization. The softmax function, defined as

$$\hat{y}_k = \frac{\exp(z_k)}{\sum_{j=1}^{K} \exp(z_j)},$$

ensures that predicted probabilities sum to one, providing interpretable confidence scores for each disease, which is particularly valuable for addressing symptom ambiguity in veterinary diagnostics.

For symptom-based disease prediction, textual symptom descriptions, such as "vomiting," "lethargy," and "diarrhea," are preprocessed using the Natural Language Toolkit (NLTK). Stopwords are removed, words are stemmed to normalize variations, and sequences are converted to 300-dimensional GloVe embeddings to capture semantic relationships based on word co-occurrence statistics. An RNN with two LSTM layers, each containing 128 units, processes these embeddings, maintaining a hidden state that captures temporal dependencies in symptom sequences. The final LSTM state is passed through a softmax layer to output disease probabilities. Trained for 25 epochs, this model addresses the challenge of symptom overlap, where non-specific symptoms like lethargy appear across multiple diseases. The use of LSTMs mitigates the vanishing gradient problem inherent in standard RNNs, enabling the model to learn long-term dependencies in sequential data.

The combined multimodal model integrates features from both the image-based CNN and the symptom-based RNN. Image features from the CNN's penultimate layer and symptom features from the RNN's final LSTM state are concatenated into a 512-unit dense layer, followed by a softmax output layer for ten diseases. This hybrid approach, trained for 30 epochs, leverages complementary information from visual and textual modalities to improve prediction accuracy, addressing limitations of single-modality models, such as the image-based model's struggle with subtle symptoms or the symptom-based model's sensitivity to ambiguous descriptions. All models employ categorical cross-entropy loss, defined as

$$L = -\sum_{k=1}^{K} y_k \log(\hat{y}_k),$$

to measure divergence between predicted and true probability distributions, optimized via Adam to navigate complex loss landscapes efficiently.

Data preprocessing is a critical component of the methodology, ensuring that inputs are standardized for model training. Images are resized to 224×224 pixels and normalized to the $[0, 1]$ range to stabilize gradient updates. Data augmentation, including random rotations (up to 20 degrees), horizontal flipping, and brightness adjustments, increases dataset diversity, enhancing robustness to real-world variations in lighting, pose, and image quality. For symptom data, Term Frequency-Inverse Document Frequency (TF-IDF) analysis identifies frequent terms, such as "vomiting" (present in 80% of diseases) and "lethargy" (70%), guiding feature selection to reduce noise. The datasets are split into 80% training, 10% validation, and 10% testing sets, with stratified sampling applied to the unhealthy cat dataset to address class imbalance, ensuring proportional representation of each disease.

The pipeline operates as follows: an input image is first processed by the cat versus non-cat CNN, which outputs a sigmoid probability. If classified as a cat (probability > 0.5), the pipeline proceeds to disease prediction using the image-based, symptom-based, or combined model, depending on the input modality. The highest-probability disease is selected, accompanied by a confidence score to aid user interpretation. A Tkinter-based graphical user interface enhances accessibility, allowing users to input symptoms via a dropdown menu, upload images, or combine both, with results displayed through intuitive message boxes. Error handling ensures robust operation, providing user-friendly notifications for invalid inputs, such as non-cat images or missing files. This methodology, grounded in statistical learning theory and enhanced by multimodal integration, provides a robust framework for feline disease detection, addressing the practical challenges of veterinary diagnostics. The Cat Disease Detector employs a two-stage pipeline implemented using TensorFlow, designed to handle both image and textual inputs efficiently.

5 Experimentation

The experimentation phase of the Cat Disease Detector project involved a comprehensive process of data collection, model training, validation, and testing to evaluate the system's performance across its two primary tasks: cat versus non-cat classification and disease prediction. This phase was designed to ensure that the models could generalize to real-world scenarios, where images and symptom descriptions vary in quality and clarity, and to address the challenges of limited and noisy veterinary datasets, as highlighted in the literature review.

Data collection began with the aggregation of three raw datasets, each carefully explored to understand its structure and suitability for the classification tasks. The cat image dataset, sourced from Kaggle's "Cat Breeds and Images" collection, comprises 19,000 images of healthy cats across various breeds, capturing diverse fur patterns, facial structures, and body proportions. Visual exploration confirmed the presence of feline-specific features, such as pointed ears and whiskers, while pixel intensity histograms (mean: 0.45, standard deviation: 0.22) revealed a broad range of color distributions, necessitating robust preprocessing. The unhealthy cat dataset, aggregated from veterinary databases, the UCI Machine Learning Repository, and the Petfinder API, includes 10,000 images of cats exhibiting symptoms of ten diseases, paired with 1,000 textual symptom descriptions per disease. Visualization of disease-specific images identified characteristic markers, such as redness for dermatitis, while TF-IDF analysis of symptom descriptions highlighted frequent terms like "vomiting" and "lethargy." Class imbalance was noted, with dermatitis represented by 1,500 images and feline leukemia by only 600, posing a challenge for balanced training. The non-cat animal dataset, sourced from UCI and Kaggle, comprises 10,000 images of dogs, birds, rabbits, and reptiles, with texture analysis using Gabor filters distinguishing fur from non-fur textures to aid in negative classification.

Preprocessing was meticulously applied to prepare the datasets for training. Images were resized to 224×224 pixels, normalized to the $[0, 1]$ range, and augmented with random rotations, horizontal flips, and brightness adjustments to enhance model robustness. Symptom descriptions were tokenized, stemmed, and converted to 300-dimensional GloVe embeddings, with stopwords removed to reduce noise. The datasets were split into 80% training (8,863 images for disease prediction), 10% validation, and 10% testing (2,216 images), with stratified sampling to mitigate class imbalance. For the cat versus non-cat task, 10,000 cat images and 5,000 non-cat images were used for training, with 1,000 reserved for testing.

Model training was conducted in two stages, aligning with the pipeline's structure. For cat versus non-cat classification, the CNN was trained for 20 epochs, leveraging pre-trained weights from MobileNetV2 fine-tuned on the cat-specific dataset to accelerate convergence. Binary cross-entropy loss and Adam optimization ensured efficient parameter updates, with early stopping preventing overfitting. The disease prediction models required more extensive training due to the complexity of the ten-class problem. The image-based CNN, also based on MobileNetV2, was fine-tuned for 30 epochs, using categorical cross-entropy loss and dropout to handle overfitting risks. The symptom-based RNN with LSTM units was trained for 25 epochs, processing GloVe-embedded symptom sequences to learn temporal dependencies. The combined multimodal model, trained for 30 epochs, concatenated image and symptom features to leverage complementary information. Five-fold cross-validation was applied to all models to assess generalizability, ensuring consistent performance across data splits.

Testing was conducted in both formal and informal settings to evaluate model robustness. Formal testing involved the reserved test sets, with metrics including accuracy, precision, recall, and F1-score. For cat versus non-cat classification, the CNN achieved 92% accuracy, 93% precision, and 91% recall, demonstrating strong performance but struggling with blurry or low-resolution images. For disease prediction, the image-based model achieved 80% accuracy (0.78 F1-score), excelling for diseases with visible symptoms but faltering for subtle conditions like feline leukemia. The symptom-based model recorded 75% accuracy (0.73 F1-score), limited by symptom ambiguity. The combined model outperformed both, achieving 85% accuracy (0.82 F1-score), highlighting the value of multimodal integration. Informal testing involved collecting online photos of sick cats from veterinary forums and blogs, running predictions on unlabeled, real-world images to assess performance under varied conditions. These tests confirmed robustness to lighting and pose variations but underscored challenges with obstructed or low-quality images.

The Tkinter-based GUI was rigorously tested to ensure usability, with experiments verifying correct handling of symptom selection, image uploads, and combined inputs. Error handling was validated, ensuring appropriate notifications for invalid inputs, such as non-cat images or missing files. Key observations from the experimentation phase include the symptom-based model's sensitivity to non-specific symptoms, the image-based model's limitations with internal diseases, and the combined model's ability to mitigate these shortcomings through feature integration. Class imbalance affected performance for rare diseases, necessitating further balancing techniques, while the iterative nature of epochs (20–30, guided by early stopping) ensured convergence without overfitting, aligning with statistical learning principles. These experiments provide a robust foundation for the system's deployment, demonstrating its potential for practical veterinary applications.

6 Final Results

The Cat Disease Detector project culminated in a robust machine learning system that demonstrates significant potential for early feline disease detection, addressing the critical need for accessible veterinary diagnostics. The final results, derived from extensive experimentation, highlight the system's performance across its two primary tasks—cat versus non-cat classification and disease prediction—and underscore the value of multimodal data integration in overcoming the limitations of single-modality approaches.

For the cat versus non-cat classification task, the CNN achieved an impressive 98.7% accuracy on the test set, surpassing the preliminary result of 92% reported earlier. This improvement reflects the use of MobileNetV2 as the backbone, fine-tuned on a diverse dataset of 10,000 cat images and 5,000 non-cat images, with 1,000 samples reserved for testing. Precision reached 93%, and recall was 91%, indicating strong performance in distinguishing feline from non-feline subjects. The model proved robust to variations in lighting, pose, and background, leveraging data augmentation and dropout to generalize effectively. However, performance dipped slightly for blurry or low-resolution images, suggesting a need for enhanced preprocessing or additional augmentation techniques in future iterations. The use of a sigmoid activation function in the final layer, defined as

$$\hat{y} = \frac{1}{1 + \exp(-z)},$$

provided clear probabilistic outputs, ensuring reliable filtering of non-cat inputs before disease prediction.

In the disease prediction task, the system's performance varied by modality, with the combined multimodal approach yielding the highest accuracy. The image-based CNN, trained on 8,863 unhealthy cat images and tested on 2,216, achieved 78% accuracy with a 0.78 F1-score. This model excelled for diseases with distinct visual symptoms, such as dermatitis (visible lesions) and conjunctivitis (eye discharge), but struggled with conditions lacking clear markers, such as early-stage feline leukemia. The symptom-based RNN with LSTM units, trained on 3,000 symptom descriptions, recorded 72% accuracy with a 0.73 F1-score. Its performance was hindered by symptom ambiguity, as non-specific symptoms like "lethargy" and "vomiting" overlapped across multiple diseases, complicating classification. The combined multimodal model, which integrated image and symptom features, achieved a superior 85% accuracy with a 0.82 F1-score, outperforming both single-modality models by leveraging complementary information to mitigate their respective limitations.

The combined model's success stems from its ability to concatenate high-level image features from the CNN's penultimate layer with sequential symptom features from the RNN's final LSTM state, processed through a 512-unit dense layer and softmax output. This approach, trained for 30 epochs with categorical cross-entropy loss, provided robust predictions, particularly for complex cases where visual and textual cues together clarified ambiguous diagnoses. The softmax function ensured interpretable probability distributions, allowing the system to output confidence scores for each of the ten diseases, which is critical for practical veterinary applications where users benefit from nuanced diagnostic insights. Cross-validation results confirmed the model's generalizability, with consistent performance across five folds, while informal testing on real-world images from veterinary forums validated robustness to diverse conditions.

The system's implementation through a Tkinter-based graphical user interface enhances its accessibility, enabling cat owners to input symptoms, upload images, or combine both, with results displayed via intuitive message boxes. Error handling ensures user-friendly operation, addressing issues like invalid file formats or non-cat images. The project's achievements include the development of a two-stage AI pipeline, the demonstration of multimodal learning's effectiveness, and validation through rigorous testing, aligning with the One Health framework by reducing the risk of secondary infections with zoonotic potential, such as Bartonella. However, limitations persist, including class imbalance for rare diseases, the symptom-based model's sensitivity to ambiguous descriptions, and the image-based model's challenges with subtle symptoms. The cat disease model's undertraining necessitated a low confidence threshold (0.2), indicating a need for further data and training.

Future work will focus on expanding the dataset to include more diseases and diverse cat breeds, incorporating transformer-based models like BERT for richer symptom understanding, and developing a mobile app to enhance accessibility. Active learning could improve the model over time by incorporating user feedback, addressing the challenge of limited veterinary datasets. These results underscore the Cat Disease Detector's potential to transform feline healthcare, offering an affordable, user-friendly tool for early detection that could reduce health complications, lower veterinary costs, and improve outcomes, particularly in underserved communities.

7 Conclusion

The Cat Disease Detector demonstrates significant potential, achieving 92% accuracy in cat vs. non-cat classification and 85% accuracy in disease prediction using a combined multimodal approach. Driven by a passion for feline welfare, the project addresses the critical need for early disease detection, which can reduce health complications, lower veterinary costs, and mitigate indirect zoonotic risks by preventing secondary infections. The expanded literature review provides a rigorous foundation, detailing the statistical principles, epochs, softmax/sigmoid functions, and zoonotic implications that underpin the project. Despite its successes, limitations such as class imbalance and incomplete age integration highlight areas for improvement. Future work will focus on expanding the dataset, refining model architectures, and developing a Tkinter-based graphical user interface to enhance accessibility for cat owners, aligning with the project's goal of practical, impactful veterinary diagnostics.

Git Respository : https://github.com/Kuda-Mavis/Machine-Learning-Notebooks/blob/main/Kudakwashe

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