Can machine learning reduce the number of unnecessary antibiotic prescriptions in veterinary practices?

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INTRODUCTION

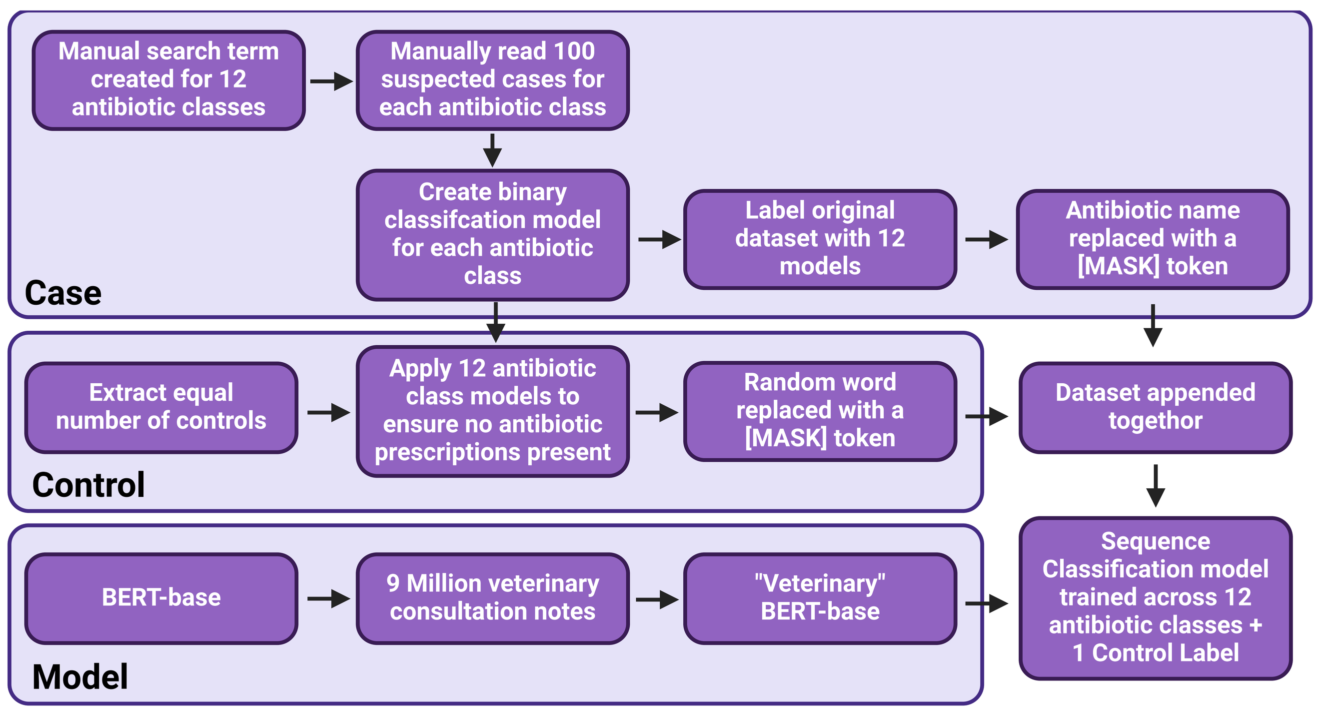
Unnecessary antimicrobial exposure leads to resistance emergence, a grave concern for the future utility of antimicrobials. Veterinary practitioners are as equally liable for the march towards antimicrobial resistance and therefore their methods of prescribing should be treated as vigorously as other prescribing entities.

Can AI illustrate what drives vets to prescribe antibiotics and find out what happens when they do ?

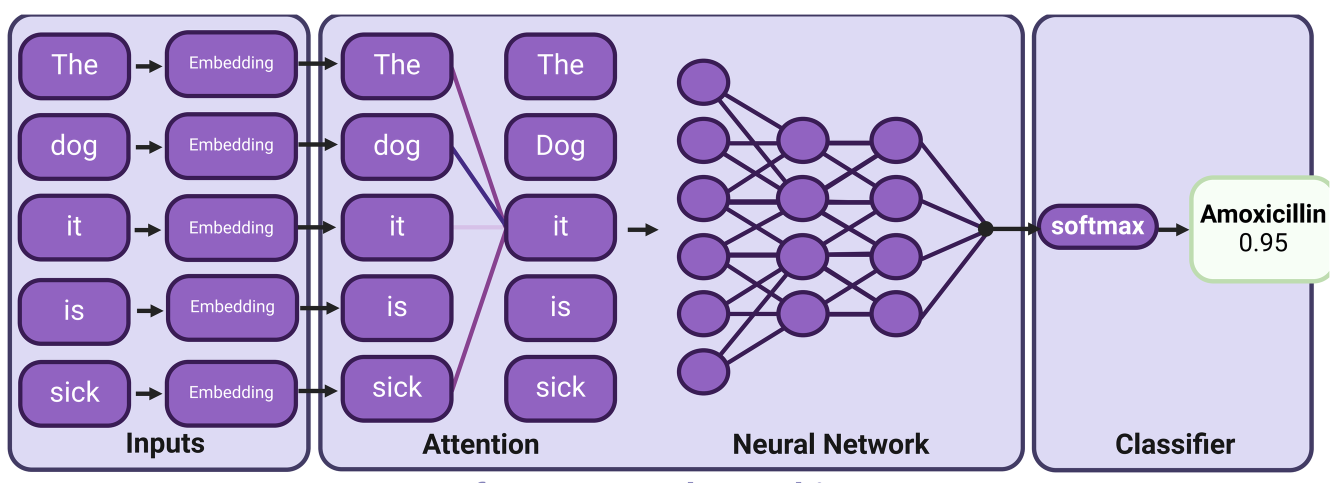
METHODS

Data Management

1. Derive generalised search term to find suspected antibiotic cases
2. Manually assign labels to subset of suspected prescibing records based on careful reading
3. Antibiotic is replaced with a [MASK] token to ensure model doesn't converge on these words alone .
4. Create control set based equal in size to number of cases. Ensure search term does not find antibiotics. Replace random word with [MASK]



Language Model



Transformer Encoder Architecture

Data is fed into BERT-base, a transformer based model (encoder architecture shown above) (1). Model was initially trained on corpus of 3.3 billion words across Wikipedia and BookCorpus, before the same training tasks (MLM/NSP) on our veterinary corpus. Finally, the model was exposed to the given of sequence classification task.

DATASET SOURCE

University of Liverpool | Small Animal Surveillence Network

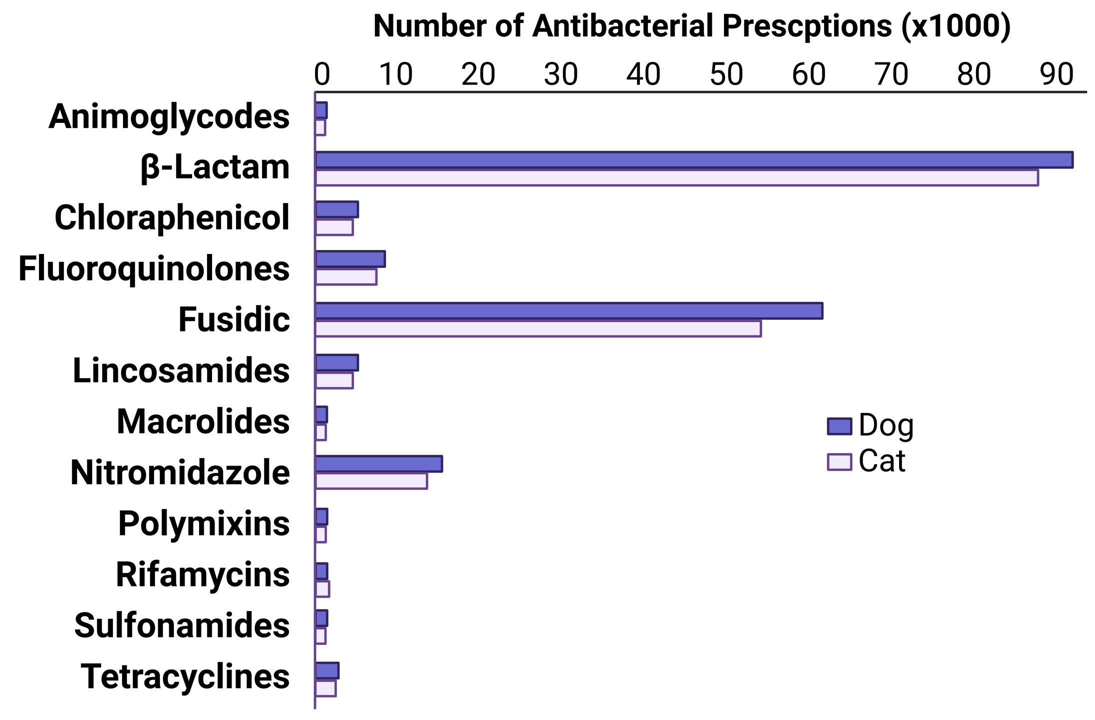
9 Million Veterinary Consultation Notes since 2014
~1 Million new records per year

Date of Birth	Owner Postcode	Practice ID	Free-text Narrative based on events during consultation
Species	Breed	Consult Date	
Insurance Status	Neuter Status	Consultation Label	

RESULTS

Model Performance Metrics = Sequence classification model trained across 12 antimicrobial classes + 1 category for narratives with no antimicrobial prescribed (left).
Prescriptions per Class = Number of antimicrobial prescriptions between dog and cat species (right)

	Precision	Recall	F1-Score
Aminoglycosides	0.94	0.99	0.99
β-Lactams	0.87	0.92	0.92
Chloramphenicol	0.94	0.54	0.54
Fluroquinolones	0.81	0.88	0.75
Fusidic	0.82	0.66	0.66
Lincosamides	0.62	0.68	0.68
Macrolides	0.68	0.64	0.65
Nitroimidazole	0.88	0.74	0.71
Polymixins	0.47	0.56	0.58
Rifamycins	0.49	0.72	0.71
Sulfonamides	0.57	0.55	0.53
Tetracyclines	0.59	0.56	0.52
Controls (No Antibiotics)	0.99	0.97	0.98
Accuracy	0.77	0.72	0.71



EXPLAINABILITY

Topic Modelling (below) - Unsupervised method to extract main topics or "themes" from a given dataset

1. Inputs are embedded using the same language model used above.
2. Reduce dimensionality of inputs together via clustering algorithm
3. The frequency of a given word within each cluster are passed into a TF-IDF model

$$w_{i,j} = tf_{i,j} \times \log\left(\frac{N}{df_i}\right)$$

4) Word with highest output become topics with with similar contextual words having similar outputs.

Here, datasets labelled with the antibiotic class by the model are passed through a BERTopic model revealing conditions associated with that (2).

Positively Contributed to the Models Prediction | Negatively Contributed to the Models Prediction

5cm patch of wet dermatitis on side, has been licking it. skin inflammed across groin, here as well, has had this problem previously. ok in self, bit quieter today. advise clean daily and apply topical [MASK] after.
Model Prediction: Fusidic Acid
Confidence: 97%
True Label: Fusidic Acid

Ears look very inflamed and sore. <<Identifier>> is scratching ears on carpet at home. Suspected otitis gave [MASK] to be taken twice everyday. Otherwise doing perfectly fine and healthy.
Model Prediction: Fluoroquinolones
Confidence: 93%
True Label: Fluoroquinolones

urinated in the house a couple of times and has blood in urine. urine passed in here on bladder palpation. blood 4+, protein+, pH5, SG 1.038. no obvious crystals seen on microscopy. quick scan of bladder no obvious masses or uroliths, treat as cystitis, start [MASK] and metacam and rv next week with repeat urine sample.
Model Prediction: β-lactam
Confidence: 93%
True Label: β-lactam

Owner brought in as <<Identifier>> has not been eating, quite an old dog so might just be age. Gave [MASK] just in case as owner very worried, told to come back if things deterioate.
Model Prediction: No Antibiotics
Confidence: 63%
True Label: β-lactam

Explainability Layer (above) - Trained model interpratbility on given inputs using integrated gradients where the difference between a blank state to the input is calculated by determining the accumulated gradients using the following equation:

$$IG(f, x_i) \equiv (x_i - x_i') \int_0^1 \nabla_i f(x_i' + \alpha(x_i - x_i')d\alpha$$

Explainability layer outputted as an overlay on text, where green representings a positive contribution to the models output and red where that phrase's presence results in the reduction in the models confidence. (3)

N.B. Final output does not match the clinician, however is this an example where the model made the better decision?

FUTURE DIRECTIONS

- Reference available guidelines when labelling initial datasets so resultant model is reflective of what should be prescribed rather than the average prescription
- Train model on non-antibiotic alternatives
- Integration of model antibiotic suggestions into clinicians management system
- Relationship of disease or clinical presentations that lead to an antibiotic being prescribed

(1) Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.
(2) Grootendorst, M. (2022). BERTopic: Neural topic modeling with a class-based TF-IDF procedure. arXiv preprint arXiv:2203.05794.
(3) Sundararajan, M., Taly, A., & Yan, Q. (2017, July). Axiomatic attribution for deep networks. In International conference on machine learning (pp. 3319-3328). PMLR.