PetEVAL: A veterinary free text electronic health records benchmark

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Abstract

We introduce PetEVAL, the first benchmark dataset derived from real-world, free-text veterinary electronic health records (EHRs). PetEVAL comprises 17,600 professionally annotated EHRs from first-opinion veterinary practices across the UK, partitioned into training (11,000), evaluation (1,600), and test (5,000) sets with distinct clinic distributions to assess model generalizability. Each record is annotated with International Classification of Disease 11 (ICD-11) syndromic chapter labels (20,408 labels), disease Named Entity Recognition (NER) tags (429 labels), and anonymisation NER tags (8,244 labels). PetEVAL enables evaluating Natural Language Processing (NLP) tools across applications, including syndrome surveillance and disease outbreak detection. We implement a multistage anonymisation protocol, replacing identifiable information with clinically relevant pseudonyms while establishing the first definiti on of identifiers in veterinary free text. PetEVAL introduces three core tasks: syndromic classification, disease entity recognition, and de-identification. We provide baseline results using BERT-base, PetBERT, and Llama 3.1 8B generative models. Our experiments demonstrate the unique challenges of veterinary text, showcasing the importance of domain-specific approaches. By fostering advancements in veterinary informatics and epidemiology, we envision PetEVAL catalysing innovations in veterinary care, animal health, and comparative biomedical research through access to real-world, annotated veterinary clinical data.

1 Introduction

The growing availability of veterinary electronic health records (vEHRs) from sources such as the Small Animal Veterinary Surveillance Network (SAVSNET) (Sánchez-Vizcaíno et al., 2015), Companion Animal Veterinary Surveillance Network (CAVSNET) (Sheng et al., 2022), and VetCompass (Royal Veterinary College (RVC); McGreevy et al., 2017) presents an unprecedented opportunity to advance veterinary medicine. These datasets support disease surveillance, epidemiological research, and clinical decision-making (Farrell et al., 2023b; Bode et al., 2022; Radford et al., 2011; Sánchez-Vizcaíno et al., 2017; Singleton et al., 2020). However, vEHRs differ from human biomedical records in syntax, lexicon, and clinical expression (Davies et al., 2024b), requiring adaptation of existing computational tools. Additionally, first-opinion vEHRs often contain diagnostic uncertainty due to limited specialist access, resource constraints, and financial considerations (Robinson et al., 2016).


```
[
    {
        "savsnet_id": 1111025,
        "text": "Brought in with Coco who has
           conjunctivitis; fluo neg. no blepharospasm or
           rubbing.otherwise nad. Adv monitor, ini send to Smith
           Referrals",
        "icd_11_chapter": "Diseases of the visual system",
        "disease_ner_entities":[[12,36,"Conjunctivitis"]],
        "anonymisation_ner_entities": [[16,20,"PER"],
           [123,138,"LOC"]]
    }
]
```


Figure 1: Example data for a single consult with a unique consult, the free text clinical EHR, the ICD-11 chapter multi-label classification and NER entities for both anonymisation and disease extraction task

Despite these challenges, vEHRs offer unique advantages for biomedical research. Unlike human records, which are tightly regulated under laws such as HIPAA and GDPR, vEHRs face fewer legal constraints (Sun et al., 2020), making them a viable testbed for developing analytical methods. Their relative accessibility enables researchers to explore novel computational approaches without the ethical and regulatory barriers associated with human health data (Kol et al., 2015; Starkey et al., 2005; Trott

et al., 2004).

Advancing natural language processing (NLP) for vEHRs is critical for global health, supporting the World Health Organisation's (WHO) One Health initiatives in zoonotic disease surveillance and antimicrobial resistance (AMR) monitoring (Bidaisee and Macpherson, 2014; Radford et al., 2011). Enhanced NLP tools improve threat detection and trend analysis in animal populations, strengthening public health responses across human, animal, and environmental health domains (Kol et al., 2015; Robertson et al., 2000; Van Duijkeren et al., 2004). Beyond public health, NLP-driven solutions facilitate large-scale epidemiological studies, identifying risk factors and treatment outcomes that enhance companion animal welfare (Lund, 2015; Farrell et al., 2023b).

Traditional veterinary disease surveillance relies on manual coding or rule-based methods, which are time-intensive and prone to human error (Hsia et al., 2010; Miñarro-Giménez et al., 2018; Turchin et al., 2006). In contrast, NLP-driven approaches offer scalable, automated solutions for extracting clinical insights from free-text records. Developing these methods within veterinary medicine improves animal welfare and contributes to the refinement of computational tools that may later be adapted to human bioinformatics research.

In this paper, we contribute the following:

1. PetEVAL: The first veterinary EHR benchmark – A publicly available free-text vEHR dataset, establishing a standard for veterinary NLP research.
2. Rigorous manual anonymisation – Every record underwent manual anonymisation with at least two independent reviews, including verification by a veterinary clinician, ensuring complete removal of sensitive data.
3. ICD-11 syndromic classification – Syndromic labels were assigned using the ICD-11 framework, supplemented with domain-specific annotations to ensure clinically relevant labeling.

2 Literature Review

The adoption of EHRs has revolutionised medical research, offering vast amounts of health data for analysis (Gunter and Terry, 2005; Cowie et al., 2017). While structured EHR data has been extensively used in epidemiological studies (Krumholz et al., 2014; Hamer et al., 2024; Hlatky et al., 2014; Williamson et al., 2020), up to 80% of EHR information exists in unstructured formats, primarily as free-text clinical notes (Kong, 2019). These unstructured notes capture clinical insights often lost in structured formats (Birman-Deych et al., 2005; Singh et al., 2004). Excluding this data from research can significantly impact the validity of findings (Ford et al., 2013; Jensen et al., 2017; Price et al., 2016; Barak-Corren et al., 2017). However, utilising unstructured data presents challenges in patient privacy protection, particularly regarding re-identification risks (Simon et al., 2019; Abouelmehdi et al., 2017; Dorr et al., 2006). Automated EHR anonymisation has become a critical focus in addressing these challenges. Benchmarks like the i2b2/UTHealth corpus and MIMIC-3 database have been established to evaluate de-identification models (Stubbs and Uzuner, 2015; Stubbs et al., 2017; Meystre et al., 2010; Aberdeen et al., 2010). Approaches range from rule-based systems (Cao et al., 2003) to neural networks (Liu et al., 2019) and pre-trained language models (Yoon et al., 2023; Chen et al., 2021). Recent advancements in learning-based methods show promise in automating de-identification (Leevy et al., 2020; Lee et al., 2022). However, these methods face challenges with performance instability when applied to heterogeneous real-world data (Abu-El-Rub et al., 2022; Yang et al., 2019). Deep learning approaches have been proposed to address these issues, but their effectiveness is limited by small training datasets and performance degradation on out-of-distribution EHRs (Syed et al., 2022; Lee et al., 2021; Jiang et al., 2017).

3 PetEval

3.1 The SAVSNET Dataset

We utilise data from the Small Animal Veterinary Surveillance Network (SAVSNET), a sentinel network of 253 volunteer first-opinion veterinary practices across the United Kingdom that have collected electronic health records (EHRs) since March 2014. This network has accumulated over 12 million EHRs, with participating practices selected based on their practice management software compatibility with the SAVSNET data exchange system. During each consultation with a clinician or nurse, comprehensive data includes species, breed, sex, neuter status, age, owner's postcode, insurance and microchipping status, and a detailed free-text clinical narrative. These narratives may contain information about symptoms, diagnoses, treatments, procedures, or other clinical

matters. Owners can opt out of data collection during any consultation. The SAVSNET group operates under ethical approval from the University of Liverpool Ethics Committee (RETH001081), ensuring adherence to established ethical standards. Figure 1 provides a sample data point in JSON format.

3.2 Tasks

3.2.1 Task 1 - Anonymisation

Ensuring the privacy and security of EHRs is crucial for safeguarding the personal information of pet owners and facilitating the easy sharing of data use in clinical and academic research. The dataset is labelled with NER entities and spans applied to pseudo-anonymised contextual placeholders. The objective is to maintain the integrity and utility of clinical information within the EHR while effectively anonymising various types of personal data. This includes names (both animal and human), location details (such as city, town, and addresses), organisation names (including attending veterinary practices, referral hospitals, kennels, and laboratories), contact details (emails, phone numbers), id-numbers (passport numbers, insurance policy numbers, MRCVS codes), and any other explicit identifiers. The anonymisation is compliant with the HIPPA Safe Harbour (Sun et al., 2020).

3.2.2 Task 2 - Syndromic Disease Classification

Given the critical role of monitoring national disease outbreaks in public health, effective surveillance systems can provide invaluable insights, such as in informing clinicians of key symptoms to observe, enabling researchers to identify aetiological agents, and establishing an automated reporting mechanism for public health agencies to facilitate swift notification of changes in disease occurrence. However, the task is not straightforward, particularly when dealing with novel diseases or syndromes with unknown symptoms. Effective outbreak reduction strategies hinge on the ability to detect outbreaks with minimal cases. To address these challenges, the dataset is provided with International Classification of Disease 11 (ICD-11) chapters (World Health Organisation (WHO), 2022), which includes contextual discussions such as symptoms and diagnoses. The task is structured as a multi-label classification problem, as a consult or condition may cover a range of presenting symptoms. Performance is evaluated using multi-label classification metrics, including precision and recall, macro-average F1-Score, and weighted F1-Score.

3.2.3 Task 3 - Disease Extraction

Identifying specific diseases is critical for downstream epidemiological studies, which aim to reveal novel risk factors, seasonality, and other trends. This task is particularly challenging due to the private healthcare nature of veterinary practices in the UK and much of the world. Confirmation diagnostic tests are rare, as owners often wish to avoid the inherent costs, opting instead to take the advice of clinicians or due to the lack of available resources or expertise not found in first opinion practice. Additionally, the presence of negations or listing of differential diagnoses complicates the task further. In our study, the dataset is labelled with the diagnostic disease contained within it. This process is framed as NER task using the IOB2 format, wherein the entity of 'disease' and its spans are provided. Evaluation utilises SeqEval for precision, recall, and F1-score (Nakayama, 2018).

4 Methods

4.1 Dataset Construction

Our dataset comprises three subsets: a training set of 11,000 records, an evaluation set of 1,600 records, and a test set of 5,000 records. We selected only consultations recorded before 2020 and restricted the dataset to consultations involving only cats and dogs. To enhance generalisability, dataset splits were performed based on a pre-compiled list of veterinary practices, following the methodology outlined in (Farrell et al., 2023a). Specifically, we assigned distinct practices to training and testing sets, ensuring that models trained on the training set were evaluated on records from veterinary practices that did not contribute to training. This design minimises the risk of models overfitting to stylistic or institutional biases and provides more substantial evidence of generalisability across UK veterinary practices. We excluded empty records containing fewer than ten words or exceeding 350 words. The median narrative length in the full SAVSNET dataset is 287 words, while in PetEVAL, it is 226 words.

4.1.1 Annonymisation

Each record was manually reviewed twice, targeting the removal of all potential identifiers, including names (owner, animal, and veterinary staff), locations (cities, countries,

Table 1: Evaluation of named entity recognition (NER) performance on veterinary clinical text data anonymised according to HIPAA Safe Harbor guidelines. The table presents entity type distribution across training, evaluation, and test splits, with comparative performance metrics (precision, recall, F1-score) between 'BERT-base-uncased', 'PetBERT', and Llama 3.1 8B models across identifier categories.

HIPAA Safe Harbor	Examples	Train/ Eval	Test Count	NER Entity	BERT-base-uncased			PetBERT			Llama 3.1 8B		
					P	R	F1	P	R	F1	P	R	F1
(A) Names	Pet, Owner, Vet Names	4790	1370	PER	0.84	0.93	0.89	0.93	0.70	0.80	0.71	0.65	0.68
(B) Geographic	City, Towns, Countries	311	94	LOC	0.95	0.98	0.97	0.97	0.97	0.97	0.78	0.83	0.80
subdivisions	Vet practices, hospitals, shelters	392	168	ORG	0.97	0.97	0.98	0.98	0.96	0.97	0.82	0.79	0.81
(C) Dates	Day/month dates, appointments	425	162	TIME	0.94	0.96	0.95	0.93	0.94	0.93	0.76	0.81	0.78
(D) Telephone numbers	Client/practice phone numbers	19	4										
(E) Fax numbers	n/a	None	None										
(F) Email addresses	Referral/client emails	9	3										
(G) Social security numbers	n/a	None	None										
(H) Medical record numbers	n/a	None	None										
(I) Health plan numbers	Insurance policy numbers	33	20										
(J) Account numbers	Microchip Numbers	299	35										
(K) Certificate numbers	MRCVS clinician codes	51	17	MISC	0.91	0.97	0.97	0.95	0.94	0.94	0.73	0.69	0.71
(L) Vehicle identifiers	n/a	None	None										
(M) Device identifiers	n/a	None	None										
(N) URLs	Website urls	None	None										
(O) IP addresses	n/a	None	None										
(P) Biometric identifiers	n/a	None	None										
(Q) Photographic images	n/a	None	None										
(R) Other identifiers	Passport numbers	34	8										

vet practices, referral hospitals, rescue centres, kennels, crematoriums, labs), dates (when they included specific years), times (if overly specific), and unique identifiers such as microchip codes, passport numbers, insurance policy numbers, vet MRCVS codes, phone numbers, and email addresses. Flagged elements were pseudonymised with context-appropriate placeholders to maintain record coherence, and corresponding spans and entity tags were generated for these placeholders. For the anonymisation NER task, identifiers were mapped to standard tags: 'LOC' (cities, towns, countries), 'PER' (pet/owner/vet names), 'TIME' (specific dates/times), 'ORG' (veterinary practices, rescue shelters, labs, groomers), and 'MISC' (unique identifiers like microchips, insurance codes, contact information). The counts for each can be found within table 1. Non-clinical brand names were removed but not included in anonymisation metrics. No clinically relevant information was modified.

4.1.2 Syndromic Disease Classification

The dataset was curated to support syndromic disease surveillance through the assignment of International Classification of Diseases, 11th Revision (ICD-11) labels. For this purpose, 20 ICD-11 chapter codes were selected to capture a broad range of clinically relevant syndromes observed in veterinary practice. These labels were integrated into the dataset alongside the ongoing anonymisation process to ensure compliance with data protection standards. The full list of selected chapter codes is provided in Table 2. To facilitate efficient and accurate annotation, we employed a semi-automated approach wherein initial fuzzy labels were generated using the PetBERT-ICD model, a previously developed tool designed for assigning ICD-related labels in veterinary contexts. This pre-annotation step helped streamline the annotation process, reduce cognitive load for annotators, and minimise potential errors. Annotators reviewed and refined these suggested labels, ensuring alignment with clinical documentation practices in first-opinion vEHRs. To maintain the integrity of the evaluation, the test set was exempt from automated label matching and underwent a full manual review by two expert annotators. Records that an initial reviewer was unhappy to determine the presence of a diagnosis were passed through an additional reviewer, and a consensus vote was taken. Finally, we ensured that the disease extraction dataset aligned with the syndromic dataset, an extracted disease therefore has a linked syndromic label.

4.1.3 Disease Extraction

The dataset was developed to facilitate the evaluation of disease diagnosis extraction models from first-opinion electronic health records (EHRs). Given the nature of primary care veterinary records, confirmatory diagnoses are rare, with most diagnoses being clinical assessments rather than definitive results from diagnostic testing. Therefore, any named condition mentioned in a record was annotated as a diagnosis unless explicitly negated. This includes confirmed diagnoses, differential diagnoses, and syndromic descriptions. Additionally, mentions of pathogens, such as bacteria,

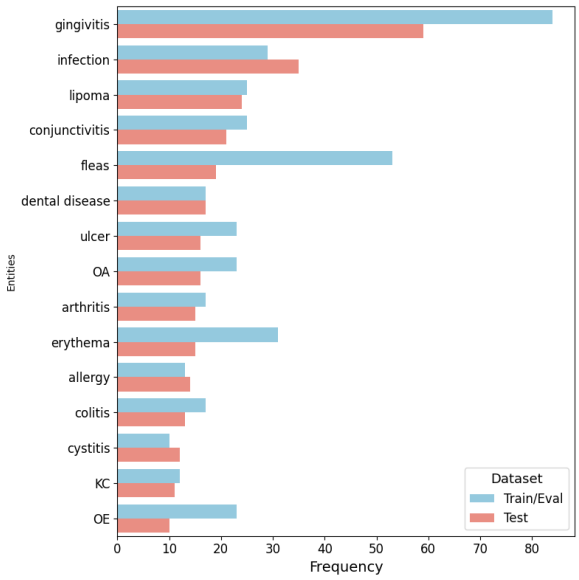

Figure 2: Distribution of the 15 most frequent disease entities extracted from veterinary electronic health records in the Train/Eval and Test sets during Task 2 (Disease Extraction).

viruses, and parasites, were annotated as they typically are discussed as diagnoses within the narratives. We extracted diseases coded within the ICD-11 and veterinary-specific conditions not represented in human medicine. The annotation process was conducted alongside the ongoing anonymisation of the dataset to safeguard patient confidentiality. Each annotated diagnosis was linked to its corresponding span within the text, with entity tags assigned to support named entity recognition (NER) tasks. Records that an initial reviewer was unhappy to determine the presence of a diagnosis were passed through an additional reviewer, and a consensus vote was taken.

4.1.4 Baseline Models

For baseline results in PetEVAL, we evaluated three pre-trained language models: 'BERT-base-uncased' (Devlin et al., 2019), a general-purpose encoder; 'PetBERT' (Farrell et al., 2023a), a veterinary domain-adapted encoder; and 'Llama 3.1 8B' (Team and Meta, 2024), a generalist decoder model. The encoder models were fine-tuned as token classification models using the IOB2 format for the anonymisation and disease extraction tasks, with training parameters including a mini-batch size of 32, an initial learning rate of 2e-5, and the AdamW optimiser. Early stopping was applied based on evaluation loss. For syndromic classification, both encoders were adapted for multi-label classification across 20 ICD-11 chapter codes, employing a weighted binary cross-entropy loss function with sigmoid activation to address class imbalance. Training followed the same hyperparameter setup and typically converged beyond epoch 6. An iterative threshold analysis was conducted, varying classification thresholds between 60% and 95% in 5% increments, prioritising recall to minimise false negatives. The final classifier applied an 80% threshold and was evaluated on the test set. The decoder model was prompted with few-shot examples selected from the training set, with multiple prompt designs tested against the evaluation set before application to the full test set.

4.1.5 Model Evaluation

We implemented a unified entity-level evaluation framework to ensure fair comparison between encoder (BERT) and decoder (LLaMA) architectures across anonymisation and disease extraction tasks. For encoder models, we first converted token-level IOB/BIO predictions into entity spans before applying the same entity-level F1 evaluation used for decoder models. This approach follows CoNLL methodology (Tjong et al., 2003), where all extracted entities undergo identical normalisation procedures before being exact-matched against ground truth. For both model types and tasks, we calculate precision as the ratio of correctly identified entities to total predictions, recall as the ratio of correctly identified entities to ground truth entities, and F1 as their harmonic mean. The anonymisation task evaluates the identification of privacy-sensitive entities (LOC, PER, MISC, NAME), while disease extraction assesses the recognition of standardised disease mentions. By standardising evaluation across architectural paradigms, we enable direct performance comparison while maintaining methodological rigour in assessing clinical information extraction capabilities.

For the syndromic classification task, we assess model performance using precision, recall, and F1 scores computed against ground truth labels provided by annotators. For encoder-based models, classification uses a fine-tuned ICD-11 classifier with an optimised threshold, ensuring a balance between precision and recall for robust disease detection. For generative models, we convert outputs into a tabular format using a direct match approach on uncased text. Similarity-based methods were considered, but they yielded no performance gains, so we adopted the least computationally intensive approach. The predicted labels are transformed into a one-hot encoded vector, applying the same evaluation metrics as encoder models.

Given the importance of disease surveillance, we preferentially select for recall to minimise false negatives, as missing cases could lead to undetected outbreaks. While this may increase false positives, these can be further reviewed to ensure the detection of potential health threats.

5 Results

5.1 Corpus Overview

The dataset consists of 675,935 words distributed across the training (11,000 records), evaluation (1,600 records), and test sets (5,000 records). While demographic data is not included, 68% of the records represent dogs, with a near 50-50 sex split across both species. The dataset contains information from 16,153 unique animals from various regions across the UK.

For syndromic disease classification, annotations were applied using a multi-label one-hot encoding approach aligned with ICD-11 chapter heads. Across the dataset, 9,510 annotations were made in the training set and 4,714 in the test set. The most frequent label, 'Certain infectious or parasitic diseases', was prominent due to the high occurrence of conditions like parasitic infestations. The median labels per class in the training set was 348, with an average of 0.9 labels per consultation. Notably, 8,907 consultations received at least one label, while those without a label typically represented routine checkups or non-syndromic cases.

The frequency distribution of extracted disease entities across the train/eval and test datasets is presented in Figure 2. As expected, conditions readily identifiable through visual examination, such as gingivitis, conjunctivitis, and lipoma, exhibit high representation. Furthermore, the extracted entities encompass clinical language commonly used by veterinary practitioners to indicate disease, including terms like 'infection,' 'fleas' (for flea infestation), and 'dental disease' (for unspecified dental conditions). The train/eval datasets contain 3,907 unique extracted conditions, while the test dataset comprises 2,899.

5.2 Inter-annotator agreement

Inter-annotator agreement was assessed on a subset of 1,000 vEHRs from the test set focused on the syndromic classification task. Two expert veterinary clinicians independently annotated the records using strictly predefined guidelines, with no communication allowed at this stage to ensure unbiased annotations. The resulting Cohen's kappa statistic was 0.722, indicating a substantial level of agreement (McHugh, 2012). This value suggests strong, though not perfect, alignment between the annotators. Disagreements were systematically reviewed, with the majority resolved through a collaborative discussion. In cases where consensus could not be reached, a third clinician provided a decisive resolution.

5.3 Baselines

We conducted baseline experiments with 'bert-base-uncased' and 'PetBERT' and a generative model 'Llama 3.1 8B' to establish reference points for evaluating more complex models. For the anonymisation task, PetBERT consistently outperformed BERT-Base across HIPAA Safe Harbor entity categories, with notable improvements in identifying names (F1: 0.80 vs. 0.89) and geographic subdivisions (F1: 0.97 vs. 0.98) (Table 1). Both models achieved high performance in structured entity types such as dates (F1: 0.93 vs. 0.95) and organizations (F1: 0.97 vs. 0.98). LlaMA 3.1, using few-shot prompting (Appendix), was behind with lower F1-scores across all categories, particularly for names (F1: 0.68) and locations (F1: 0.80).

As shown in Table 1, fine-tuned PetBERT outperformed BERT-base-uncased across most entity types, achieving a higher precision (0.93 vs. 0.84), recall (0.70 vs. 0.93), and F1-score (0.80 vs. 0.89) for identifying personal names (PER) such as pet, owner, and vet names. In contrast, LLaMA 3.1 achieved lower performance across all entity types, with an F1-score of 0.68 for names. For location (LOC) and organisation (ORG) entities, PetBERT outperformed BERT-base-uncased, achieving F1-scores of 0.97 and 0.97, respectively, compared to BERT-base's 0.97 and 0.98. LLaMA 3.1 showed lower performance in both entity types, with an F1 of 0.80 for LOC and 0.81 for ORG. The comparison highlights PetBERT's superior ability to process veterinary clinical text, particularly for identifying personal and organisational entities, while Llama 3.1's performance in entity recognition remained behind.

PetBERT outperformed both BERT-Base and Llama 3.1 for the disease extraction task, achieving a precision of 0.90, recall of 0.85, and F1-score of 0.87 (Table 1). BERT-Base trailed with 0.70 precision, 0.55 recall, and an F1 of 0.60, while Llama 3.1, using a few-shot prompt (Appendix), performed worst (precision: 0.60, recall: 0.35, F1: 0.40).

Table 2: Performance Metrics for BERT-base-uncased, PetBERT, and Llama 3.1 8B on ICD-11 Syndromic Chapters. P = Precision, R = Recall, F1 = F1-score

ICD-11 Syndromic Chapter	Train/ Eval	Test Count	BERT-base-uncased			PetBERT			Llama 3.1 8B		
			P	R	F1	P	R	F1	P	R	F1
Certain infectious or parasitic diseases	1549	1321	0.74	0.31	0.44	0.78	0.45	0.57	0.65	0.28	0.39
Neoplasms	774	499	0.85	0.77	0.81	0.90	0.81	0.85	0.77	0.65	0.70
Diseases of the blood or blood-forming organs	90	47	0.66	0.35	0.45	0.63	0.31	0.41	0.55	0.23	0.32
Diseases of the immune system	512	429	0.80	0.54	0.64	0.84	0.51	0.64	0.68	0.41	0.51
Endocrine, nutritional or metabolic diseases	572	305	0.67	0.60	0.64	0.69	0.60	0.64	0.58	0.45	0.51
Mental, behavioral or neurodevelopmental disorders	1121	469	0.76	0.34	0.46	0.79	0.38	0.51	0.64	0.27	0.38
Diseases of the nervous system	233	150	0.54	0.58	0.56	0.71	0.54	0.61	0.48	0.42	0.45
Diseases of the visual system	905	634	0.85	0.81	0.83	0.90	0.80	0.85	0.73	0.68	0.70
Diseases of the ear or mastoid process	700	513	0.83	0.77	0.80	0.88	0.78	0.83	0.71	0.65	0.68
Diseases of the circulatory system	276	181	0.67	0.33	0.45	0.71	0.46	0.55	0.55	0.29	0.38
Diseases of the respiratory system	459	346	0.80	0.54	0.64	0.84	0.57	0.68	0.68	0.45	0.54
Diseases of the digestive system	671	259	0.81	0.55	0.66	0.79	0.62	0.69	0.67	0.46	0.55
Diseases of the skin	1377	1018	0.81	0.62	0.70	0.88	0.60	0.71	0.69	0.51	0.59
Diseases of the musculoskeletal system or connective tissue	1171	722	0.79	0.73	0.76	0.83	0.70	0.76	0.67	0.61	0.64
Diseases of the genitourinary system	569	334	0.76	0.59	0.66	0.79	0.67	0.73	0.65	0.49	0.56
Pregnancy, childbirth or the puerperium	65	36	0.42	0.17	0.24	0.74	0.12	0.21	0.36	0.10	0.16
Certain conditions originating in the perinatal period	39	27	0.50	0.08	0.13	0.00	0.00	0.00	0.38	0.05	0.09
Developmental anomalies	191	95	0.59	0.19	0.28	0.70	0.30	0.42	0.47	0.15	0.23
Injury, poisoning or certain other consequences of external causes	1113	636	0.67	0.67	0.67	0.73	0.70	0.71	0.58	0.55	0.56
micro average			**0.76**	**0.58**	**0.66**	**0.81**	**0.61**	**0.70**	**0.65**	**0.47**	**0.55**
macro average			**0.71**	**0.50**	**0.57**	**0.74**	**0.52**	**0.60**	**0.60**	**0.41**	**0.48**
weighted average			**0.76**	**0.58**	**0.65**	**0.81**	**0.61**	**0.69**	**0.65**	**0.47**	**0.54**

6 Discussion

In veterinary first-opinion clinical practice, the challenge of extracting meaningful insights from EHRs is compounded by several notable factors. Among these is the absence of standardised data conventions within free-text inputs, and inconsistencies in spelling and abbreviations used by different clinicians (Davies et al., 2024b). This is amplified by the ambiguity surrounding the interpretation of consultation events. Specifically, the lack of diagnostic details in these narratives introduces additional layers of complexity. The moderate Cohen's kappa score of 0.7, observed between two annotators—both qualified veterinary clinicians - underscores the inherent difficulties in annotating such unstructured data. Veterinary EHRs are packed with ambiguous language, clinician-specific abbreviations, and varying documentation styles, inhibiting the ability to extract information from them effectively. Even among active clinicians, the interpretation of nuanced first-opinion notes can differ, primarily due to diagnostic uncertainties, incomplete patient histories, and the lack of standardised terminology. Despite these obstacles, the intrinsic value embedded within these clinical narratives is undeniable, with applications spanning disease outbreak detection and improving public health and animal welfare standards (Davies et al., 2024a; Farrell et al., 2023a).

Generative models, such as the LLaMA 3.1 8B applied in our baseline, exhibited relatively poor performance across tasks, particularly in named entity recognition (NER). This highlights the ongoing challenge of designing effective prompting strategies, requiring further research. Additionally, generative models present inherent difficulties in evaluation, as their flexible outputs may not align precisely with gold-standard annotations. While our strict direct match approach may penalise performance, maintaining fidelity to the intended prompt remains a priority. Over time, we anticipate improvements in generative architectures, which may eventually surpass the limitations observed here. However, domain-adapted encoder-based models like PetBERT demonstrated superior performance across all tasks, aligning with expectations given their targeted pretraining. Beyond accuracy, their efficiency also makes them preferable for everyday deployments, especially in resource-intensive applications such as continuous disease surveillance. Given the significant environmental cost of running large LLMs (Bashir et al., 2024), there is a clear need for lightweight, domain-specific solutions that can operate effectively on consumer-level hardware, ensuring sustainability and practical usability in real-world veterinary informatics.

Strict privacy regulations in human healthcare restrict many studies to single institutions, creating discrepancies between reported performance and cross-site generalisability. PetEVAL collates from over 250 UK practices with diverse clinical approaches and provides substantial advantages for robust model evaluation. While fewer than 23% of human healthcare ML studies utilise multi-institutional data (McDermott et al., 2021), often resulting in signifi-

cant biases and performance degradation when applied to external institutions (Barak-Corren et al., 2021; Burns and Kheterpal, 2020), PetEval's multi-institutional framework can capture practice variability and thus offers an opportunity to assess model robustness across institutions, ultimately contributing to more accurate and equitable AI-driven healthcare systems within and beyond veterinary medicine.

7 Conclusion

PetEVAL is the first benchmark dataset for veterinary EHRs, featuring expert-annotated resources across ICD-11 syndromic classifications, disease entity recognition, and anonymisation labels. Beyond addressing a critical gap in veterinary medicine, PetEVAL facilitates valuable comparative studies between animal and human health domains, promoting cross-disciplinary insights. As a foundational resource for veterinary informatics, this dataset promises to catalyse advancements in clinical decision support systems, enhance epidemiological surveillance capabilities, and strengthen One Health initiatives, ultimately advancing animal welfare and public health research outcomes.

8 Acknowledgements

«lab details»

9 Limitations

Despite rigorous quality control, annotation errors are unavoidable due to the dataset's scale. Models trained on first-opinion vEHRs are inherently limited by the availability and accuracy of recorded information, often lacking confirmatory diagnostics due to financial constraints or resource limitations. Our evaluation method enforces strict token-level matching, penalising incomplete spans even when semantically close to the ground truth. While this is critical for anonymization, it may be overly rigid for disease extraction. Similarly, our classification approach adheres strictly to predefined categories, which, while justified by the prompt, may overlook minor deviations. Future work could explore more flexible evaluation metrics and incorporate referral-level vEHRs to enhance diagnostic certainty.

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10 appendices

10.1 Task 1: Anonymisation Prompt

Prompt: Extract Named Entities from Veterinary EHRs You are given short free-text veterinary electronic health records (EHRs). Your task is to extract named entities mentioned in the text. Focus on identifying Names (NAME) locations (LOC), organizations (ORG), temporal expressions (TIME), and miscellaneous named entities (MISC). Examples:
Input: "Raven GA castrate. Anaes: Premed ACP/Meth. Induced propofol maint iso/02. Good anaesthetic. Op: Routine open castrate. double ligated 2-0 polysorb. Skin closed intradermal." Output: RavenNAME = Raven LOC = ORG = TIME = MISC = Input: "Waffle/MG - back end irritation. Owner reports irritation round back end, rubbing bottom over last 2-3 weeks." Output: NAME = Waffle LOC = ORG = TIME = last 2-3 weeks MISC = Input: "Adv routine haem/biochem (est £603) owner will discuss with wife. - Prescription -. Date: Apr 3, 2002. Vet: Reese, Qualifications: MRCVS." Output: NAME = Reese LOC = ORG = TIME = Apr 3, 2002 MISC =
Guidelines: -Extract only named entities in the appropriate categories:
NAME: Pet Names, Owner Names, Clinain names LOC: geographical locations, clinics, hospitals, animal shelters ORG: veterinary practices, laboratories, pharmaceutical companies TIME: dates, time periods, durations, temporal references MISC: animal names, medications, procedures, medical equipment, qual-

ifications - List each entity under its proper category. - If multiple entities of the same type are mentioned, extract each one separately. - Maintain the exact form as mentioned in the text.

10.2 Task 2: Syndromic Disease Classification Prompt

You are given a free-text veterinary electronic health records (EHRs). Your task is to assign a ICD-11 chapter names based on the conditions, symptoms, and diagnoses mentioned in the text. Each assigned chapter should correspond to the primary system or disease category affected.
ICD-11 Chapters: 1. Certain infectious or parasitic diseases 2. Neoplasms 3. Diseases of the blood or blood-forming organs 4. Diseases of the immune system 5. Endocrine, nutritional, or metabolic diseases 6. Mental, behavioral, or neurodevelopmental disorders 7. Sleep-wake disorders 8. Diseases of the nervous system 9. Diseases of the eye and adnexa 10. Diseases of the ear and mastoid process 11. Diseases of the circulatory system 12. Diseases of the respiratory system 13. Diseases of the digestive system 14. Diseases of the skin 15. Diseases of the musculoskeletal system or connective tissue 16. Diseases of the genitourinary system 17. Conditions related to sexual health 18. Pregnancy, childbirth, or the puerperium 19. Certain conditions originating in the perinatal period 20. Developmental anomalies 21. Symptoms, signs, or clinical findings not elsewhere classified 22. Injury, poisoning, or certain other consequences of external causes 23. External causes of morbidity or mortality 24. Factors influencing health status or contact with health services
Examples:
1. Input: "marked signs of renal failure. not eating much. huge wt loss. not moving around much." Output: Disease of the genitourinary system
2. Input: "Bilat OE. Mild, cleaned and wax removed, no obvious sign mites. Start on ear drops, rv sooner if concerned otherwise at next vaccination on 29th." Output: Diseases of the ear and mastoid process
3. Input: "skin lesions, bloods for meds check. noticed spot like skin lesions on forehead and side of face. not rubbing/scratching. would like checked. mass on R flank, slow growing, separated masses now merged together. pulsing meloxaid for stomatogingvitis." Output: Disease of the digestive system, Disease of the skin, Neoplasms
Guidelines: - Assign at least one ICD-11 chapter name that best represents the condition(s) described. - If no condition is present then return 'None' - If multiple conditions from different systems are mentioned, include multiple ICD-11 chapter names. - Ignore non-diagnostic text (e.g., medication instructions or routine check-ups) unless relevant to a condition. - Maintain consistency in ICD-11 chapter naming as per the official classification.

10.3 Task 3: Disease Extraction Prompt

You are given a free-text veterinary electronic health records (EHRs). Your task is to **extract the disease names** mentioned in the text. Focus on identifying diseases or conditions specifically mentioned, ignoring general symptoms, treatments, or non-diagnostic text.
Examples:
1. Input: "marked signs of renal failure. not eating much. huge wt loss. not moving around much." Output: renal failure
2. Input: "Bilat OE. Mild, cleaned and wax removed, no obvious sign mites. Start on ear drops, rv sooner if concerned otherwise at next vaccination on 29th." Output: OE
3. Input: "skin lesions, bloods for meds check. noticed spot like skin lesions on forehead and side of face. not rubbing/scratching. would like checked. mass on R flank, slow growing, separated masses now merged together. pulsing meloxaid for stomatogingvitis." Output: Skin-skin lesions, stomatogingvitis, mass on R flank
Guidelines: - Extract only disease names (e.g., "Renal failure", "Otitis externa", "Neoplasm"). - Do not include symptoms, treatment plans, or general findings (e.g., "not eating much", "Start on ear drops"). - If multiple diseases are mentioned, extract each disease separately. - Maintain consistency in naming diseases and conditions as per medical terminology.