Advancing Precision Livestock Agriculture Harnessing Generative AI for Enhanced Animal Behaviour Recognition

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PROPOSED PROCEDURE

- Idea: Develop generative AI models to synthesize realistic data, simulating effects of various factors on cattle health and welfare
- Importance: Enable proactive assessment of future challenges in livestock farming







SENSOR DATA - KEY FEATURES & COLLECTION

- Data from an experiment conducted at the University of Queensland's Darbalara Farm
- Data obtained using a 3-axis accelerometer on a smart collar tag called eGrazor
- eGrazor is specifically designed for monitoring livestock



Data Generation

Behaviour Classification

Welfare Evaluation

23 cattle were fitted with eGrazor collar tags

• eGrazor captured 50 measurements per second over a span of **30 days**

REASONS TO CHOOSE GENAI

- Efficiently process large amounts of data:
 - Accelerometer data is available with around 50 measurements per second
- Generating data for unseen scenarios:
 - Generative models learn relationships and important characteristics without complex parameter tuning
 - Simultaneously generate realistic data

• Effective adaptation of the transformer architecture:

- Utilize existing models & structures
- Easily adapt models to our data

DERIVE CATTLE BEHAVIOUR

- Deep Learning models enable precise insights into cattle welfare
- Detected behavioural changes detected through these models can indicate health issues,

INNOVATE WITH EXISTING MODELS

- Leverage already existing Transformer models designed for time series data
 - Utilize accelerometer data as time series data
 - Apply established Transformer models tailored for time series analysis:
 - Effectively manage seasonal patterns in the data
 - Identify and learn trends within the data
 - Chosen model for initial implementation: Autoformer
 - Autoformer model:
 - Transformer-based model
 - Specific to time series forecasting
 - Capable of learning temporal patterns, seasonalities and trends

- enhancing early intervention strategies
- Deep Learning models outperform traditional models in accuracy despite their computational demands



RESULTS

- Promising initial results:
 - Autoformer demonstrates effectiveness in capturing underlying patterns
 - Predicted values (orange) generally align well with actual values (blue), indicating high accuracy in trend prediction
- Performance metrics:
 - RMSE of 0.503 and MedAE of 0.239, both indicating high accuracy
 - Each training iteration took approximately 0.5 seconds on an Intel Xeon CPU
 - Training on one hour of data (~180,000 points) took around six hours
- Challenges identified:
 - Discrepancies at peaks where predicted values diverge from actual values indicating difficulty in handling abrupt changes
 - Sensitivity to data fluctuations, accurately predicting smaller peaks but struggling with larger spikes



CONCLUSIONS

Promising results:

 Initial implementation of the Autoformer model shows promise, despite limited data

Current challenges:

Difficulty in predicting extreme values, especially at higher data ranges

Planned improvements:

 Adjust model architecture and fine-tune hyperparameters to improve performance in capturing rapid changes and high-magnitude values

Dataset and feature expansion:

- Extend dataset to cover longer periods for deeper insights (seasonal patterns and routine cattle behaviours)
- Integrate additional features for enhanced analysis and predictive power
- Future research:
 - Explore alternative solutions to reduce computational costs
 - Enable more efficient training of larger datasets over extended periods



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