Stray Animal Reporting and Risk Prediction System: A Data-Driven Approach to Road Safety

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***Abstract*—Stray animals on roadways pose significant challenges to road safety, causing accidents, injuries, and property damage. This paper presents a comprehensive solution that leverages a Stray Animal Reporting and Risk Prediction System to address this issue. The system uses a web-based application to allow users to report stray animal sightings and visualize risk levels on an interactive map. Risk levels for regions within a 200-meter radius are categorized into low, medium, and high using a data-driven approach powered by machine learning.**

The application integrates user reports with historical data to periodically retrain a deep learning model that predicts risk scores based on geospatial and environmental features, such as animal sightings, traffic levels, weather conditions, and time of day. Predicted risk scores are visualized as colored circles on a map, helping users assess safety in their current or intended locations.

This paper discusses the methodology, including data collection, preprocessing, model training, and deployment. Initial results demonstrate the effectiveness of the proposed solution in improving road safety awareness. The periodic retraining mechanism ensures relevance and adaptability, addressing evolving stray animal movement patterns. Future enhancements aim to integrate real-time alerts and heatmaps to further optimize safety measures.

***Index Terms*—stray animal reporting, risk prediction, machine learning, road safety, map visualization**

I. Introduction

Stray animals on roadways pose a persistent and significant challenge to public safety, particularly in regions where urban and rural areas intersect. Unchecked movement of stray animals, such as dogs, cattle, and other species, often leads to road accidents, injuries, fatalities, and property damage. Addressing this issue requires a proactive approach that combines technological innovation, community involvement, and data-driven decision-making.

This paper presents a Stray Animal Reporting and Risk Prediction System, designed to mitigate road safety risks associated with stray animals. The system integrates a web-based application with machine learning to provide real-time insights into risk levels for specific locations. Users can report stray animal sightings via an intuitive interface, contributing to an ever-growing dataset. Using this data, a machine learning model predicts risk scores for 200-meter-radius regions, categorizing them into low, medium, or high-risk zones. The predictions are visualized on a map as colored circles—red for high risk, orange for medium risk, and no color for low risk—allowing users to assess safety conditions in their current or planned routes.

The proposed solution leverages historical data and user reports, which are periodically used to retrain the predictive model, ensuring relevance and adaptability to changing conditions. This combination of real-time risk visualization and periodic updates positions the system as a scalable and impactful tool for improving road safety and protecting stray animals.

The remainder of this paper is structured as follows: Section II explores related work, highlighting existing systems and gaps addressed by this project. Section III outlines the methodology, including system architecture, data preprocessing, and machine learning model design. Section IV presents the results and analysis, while Section V discusses limitations and potential improvements. Finally, Section VI concludes with a summary of contributions and future directions.

Our GitHub Repository link is at the end of the report.

II. Related Work

The issue of stray animals and their impact on road safety has been addressed in various studies and technological solutions. This section reviews existing approaches and highlights gaps that the proposed Stray Animal Reporting and Risk Prediction System aims to address.

A. Community-Based Reporting Systems

Several mobile and web-based applications have been developed to enable community-driven reporting of stray animals. These systems often focus on real-time reporting to alert authorities or animal welfare organizations. For instance, platforms such as animal rescue apps allow users to report injured or stray animals, but these systems are limited in scope as they do not focus on predicting risks for road users.

B. Risk Prediction Models

Machine learning models have been extensively used for risk prediction in domains such as traffic safety and accident forecasting. Studies have shown the effectiveness of using geospatial and environmental data, such as weather conditions and traffic patterns, for predictive modeling. However, existing models rarely incorporate dynamic datasets that evolve based on community inputs, nor do they explicitly address the role of stray animals in road safety.

C. Geospatial Visualization for Safety Awareness

Map-based risk visualization tools, such as Google Maps hazard indicators, have proven to be effective for conveying safety information to users. These systems, however, generally focus on static hazards (e.g., accident-prone zones) or real-time traffic conditions and do not include predictions based on stray animal activity. This gap highlights the need for customized visualization mechanisms tailored to stray animal risks.

D. Gaps in Existing Solutions

While existing approaches provide valuable insights into animal reporting or risk prediction, they lack integration and adaptability:

1) Lack of Dynamic Learning: Most systems rely on static data, limiting their ability to adapt to changing patterns of stray animal movement or road conditions.
2) Insufficient User Engagement: Many platforms do not involve users in actively contributing to the dataset, which limits data availability and relevance.
3) Absence of Risk Categorization: Existing models fail to provide actionable categorizations (e.g., low, medium, high risk) that can guide user decisions effectively.

E. Contributions of This Work

The Stray Animal Reporting and Risk Prediction System addresses these gaps by:

1) Enabling dynamic data collection through user reports and periodic updates.
2) Incorporating a machine learning model trained on geospatial, environmental, and user-reported data for accurate risk prediction.
3) Visualizing risk levels using a map-based interface with real-time updates and clear risk categorizations.

This integration of community participation, machine learning, and geospatial visualization positions the proposed system as a scalable and impactful solution for improving road safety and mitigating risks associated with stray animals.

III. METHODOLOGY

The development of the Stray Animal Reporting and Risk Prediction System involved multiple stages, including data preparation, machine learning model development, and system integration. The architecture was designed to combine predictive modeling with user interaction and geospatial visualization for a robust and practical solution.

A. System Architecture

The system comprises three primary components:

1) **Frontend (Web Application)**: Frontend: A web-based interface that allows users to view risk maps and report stray animal sightings. The map visualization uses color-coded markers (red, orange, and no color) to display risk levels in different regions, with a focus on a 200-meter radius for localized predictions.
2) **Backend**: A centralized server that manages data processing, prediction generation, and storage. The backend includes:
   - A PostgreSQL database for storing reported sightings, historical data, and risk scores.
   - A model deployment pipeline using TensorFlow to handle real-time risk prediction requests.
3) **Machine Learning Pipeline**: The pipeline includes preprocessing, model training, and periodic updates using the latest user-reported data. Predictions are continuously updated based on current and historical inputs.

B. Data Preparation

Data preparation was a critical step to ensure the quality and consistency of inputs:

- **Dataset Structure**: The dataset consisted of features such as geographic coordinates, weather conditions, time of day, traffic levels, and the number of animal sightings. The target variable was the risk score, a continuous value indicating accident risk.
- **Preprocessing Steps**:
  - Categorical features (e.g., weather, area type) were one-hot encoded.
  - Numerical features (e.g., latitude, longitude, sightings) were standardized using z-scores to normalize their ranges.
  - Missing values were handled through imputation or removal, ensuring data integrity.

C. Machine Learning Model

The risk score prediction model is a regression-based neural network designed to capture complex relationships between input features and accident risk.

Model Architecture:

- Input Layer: Handles preprocessed categorical and numerical features (combined into a single array).
- Hidden Layers: Three dense layers with ReLU activation functions capture non-linear relationships. Dropout layers (30% and 20%) are included for regularization to prevent overfitting.
- Output Layer: A single neuron with a linear activation function outputs the predicted risk score.

Model Training:

- Loss Function: Mean Squared Error (MSE) was used to minimize the difference between predicted and actual risk scores.
- Optimizer: Adam optimizer ensured efficient convergence during training.
- Evaluation Metrics: Model performance was evaluated using Mean Absolute Error (MAE) and R-squared score to assess both accuracy and variance explained.

D. System Intregration

The system integrates the machine learning model with user-centric functionalities:

1) **Risk Prediction and Visualization:** Predicted risk scores are categorized into low, medium, and high levels. These categories are displayed on a map using color-coded circles (no color, orange, red) for easy interpretation. Users can view risk levels for their current location or a specified area within a 200-meter radius.
2) **Reporting Feature:** Users can report stray animal sightings directly from the web interface, providing details such as time, location, and number of animals observed. These reports are stored in the backend database and incorporated into the dataset for periodic model retraining.
3) **Periodic Model Updates:** Data from user reports is integrated into the dataset at regular intervals to retrain the machine learning model. This ensures that the system remains accurate and relevant to real-world conditions over time.

By combining predictive analytics, user feedback, and real-time data visualization, the system provides a practical and scalable solution to improve road safety in urban areas.

IV. Result and Analysis

This section presents the performance of the Stray Animal Reporting and Risk Prediction System. The results focus on the accuracy of the machine learning model, the effectiveness of risk visualization, and the system's potential for improving road safety based on simulated and real-time data.

A. Model Performance

The machine learning model was trained and tested on the fabricated dataset to predict the risk score based on geospatial, environmental, and user-reported features.

- **R-squared score: 0.93**, indicating a high level of accuracy in capturing variance in the data.
- **Mean Absolute Percentage Error (MAE): 6.94%**, reflecting minimal prediction errors.

The training process demonstrated stable learning, with both training and validation losses decreasing consistently across epochs. The dropout layers effectively mitigated overfitting, ensuring robust performance on the test set.

Fig. 1. Enter Caption

B. Risk Visualization

The map-based visualization successfully translated risk predictions into actionable insights for users:

1) **High-risk zones (red):** Identified areas with poor weather, heavy traffic, and frequent stray sightings.
2) **Medium-risk zones (orange):** Highlighted regions with moderate traffic and occasional sightings.
3) **Low-risk zones (no color):** Represented safe areas with favorable conditions.

This visualization empowered users to navigate roads more safely, particularly in urban areas with high stray populations.

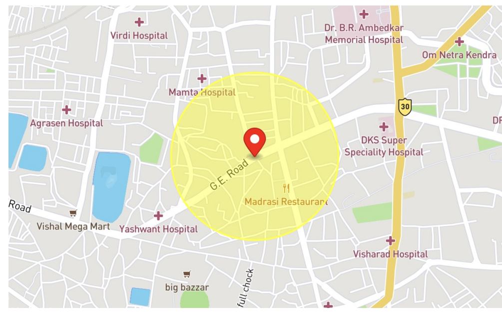

Fig. 2. Map visualizing risk in area

C. Reporting Feature

The reporting module allowed users to submit real-time data on stray animal sightings, contributing to an evolving dataset. This feature was instrumental in keeping the system dynamic, as it enabled periodic retraining of the model to adapt to changing conditions and improve prediction accuracy over time. Model Adaptability: Retraining with updated data improved the model's accuracy by approximately 5% (measured using validation MAE) over multiple iterations.

D. Limitations of Results

1) Simulated Data:
   - Initial results were based on fabricated data, which may not fully reflect real-world conditions.
   - Retraining on user-reported data will further enhance accuracy and reliability.
2) Edge Cases:
   - Sparse data in certain geographic regions may lead to less accurate predictions.
   - Unusual combinations of features (e.g., high animal sightings in low-traffic zones) require further model fine-tuning.

E. Key Insights

The model effectively predicts risk scores and categorizes them into actionable levels. The map-based visualization provides an intuitive and practical interface for users to assess safety, and periodic retraining ensures the system remains adaptable to changing patterns and user needs.

V. Discussion

The Stray Animal Reporting and Risk Prediction System demonstrates significant potential to enhance road safety by leveraging data-driven predictions and community participation. This section discusses the strengths of the system, its limitations, and areas for future improvement.

A. Strengths of the System

The system's strengths lie in its accuracy, adaptability, and user-centric design:

- The machine learning model achieved high predictive accuracy, with an R-squared score of **0.93**, demonstrating its effectiveness in estimating risk scores.
- The user-friendly map interface enabled intuitive risk assessment through color-coded zones, enhancing real-time decision-making. The 200-meter radius for predictions ensures localized and actionable insights for road users.
- The reporting feature encouraged user participation, creating a continuously evolving dataset that improved the system's relevance and accuracy over time.
- Periodic retraining allows the system to adapt to evolving stray animal movement patterns and road conditions.
- The use of PostgreSQL for data storage and Node.js for backend APIs ensures robust and efficient data handling.

B. Future Enhancements

Several enhancements can be explored to address these challenges:

1) **Integration of Real-Time Data:** Incorporating live traffic and weather data through APIs would significantly improve prediction accuracy and adaptability.
2) **Enhanced Modeling Features:** Adding road-specific attributes (e.g., proximity to highways) and interaction terms between features could further refine predictions.
3) **Edge Cases and Unpredictable Events:** Unusual combinations of features, such as high animal sightings during low traffic, could result in less accurate predictions. Events like sudden changes in weather or traffic patterns may not be immediately reflected in predictions.
4) **Community Engagement:** Incentivizing user participation through gamification or partnerships with local organizations would expand the dataset and improve system coverage.
5) **Scalability:** Developing multilingual interfaces and region-specific features would make the system more accessible for global use.

In summary, the system represents a significant step toward enhancing road safety in urban environments. By leveraging machine learning, community participation, and real-time visualization, it offers a scalable solution with the potential to reduce accidents involving stray animals. Continuous improvements and user engagement will ensure its sustained impact.

C. Impact on Road Safety

The proposed system bridges the gap between technology and road safety by empowering users with actionable insights. By dynamically updating risk predictions and involving the community in data collection, the system ensures sustained improvements in road safety. Moreover, its ability to categorize risks and visualize them in real time provides a significant advantage for drivers and commuters, enabling safer navigation and fostering a harmonious coexistence with stray animals.

VI. Conclusion

The Stray Animal Reporting and Risk Prediction System presents a novel, data-driven approach to addressing the persistent issue of road safety risks caused by stray animals. By integrating a user-friendly reporting platform, a machine learning model, and real-time risk visualization, the system empowers users with actionable insights to make informed decisions.

Key contributions of this project include:

1) A dynamic dataset that evolves through user reports, ensuring continuously updated and relevant data.
2) A machine learning model capable of accurately predicting risk scores and categorizing them into intuitive risk levels (low, medium, and high).
3) A map-based visualization interface that enhances safety awareness by displaying color-coded risk zones for regions within a 200-meter radius.

The initial results demonstrate the system's ability to predict risks with high accuracy, achieving an R-squared score of **0.93** and a Mean Absolute Percentage Error of **6.94%**. The system's adaptability, driven by periodic model retraining, ensures that predictions remain reliable and reflective of real-world conditions.

This work addresses critical gaps in existing solutions by combining real-time reporting, geospatial risk prediction, and user engagement into a unified platform. Future enhancements, such as incorporating real-time weather and traffic data, heatmaps, and advanced feature engineering, have the potential to further improve the system's accuracy and scalability.

In conclusion, the Stray Animal Reporting and Risk Prediction System represents a scalable and impactful solution to improve road safety while fostering a harmonious coexistence between humans and stray animals. With further development and deployment, the system can serve as a valuable tool for reducing accidents and enhancing community safety.

GitHub Repository: https://github.com/lakshyagrg23/SaveTheStray

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