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Automated Machine Learning and Ensemble Learning for Sentiment Analysis of Cat breeds

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Abstract : Sentiment analysis is a significant task of natural language processing (NLP) that allows the opinion extraction and classification from text data. In this study, we explore the utilization of automated machine learning (AutoML) and ensemble methods for sentiment analysis of online cat breed discussions. With AutoGluon, we automate model choice and hyperparameter optimization to develop an efficient classification system. In addition, we apply a two-stage ensemble learning approach where Support Vector Machine (SVM), Logistic Regression (LR), and Naïve Bayes (NB) are employed as base learners and LightGBM, Neural Networks (FastAI), and Random Forest are employed as meta-learners to enhance classification accuracy. The outcomes confirm that there is significant improvement in sentiment classification accuracy with ensemble learning and LightGBM as the most accurate performing meta-learner. The results validate the effectiveness of AutoML and ensemble methods to conduct domain-specific sentiment analysis tasks with a test accuracy rate of 98.29% and macro-averaged F1-score of 0.95. This study contributes to the advancement of sentiment analysis methods by introducing a hybrid model that combines automated model selection with advanced ensemble learning methods.

Keywords: Sentiment Analysis, AutoML, AutoGluon, Ensemble Learning, Machine Learning, Cat Breeds, NLP, Deep Learning.

INTRODUCTION

With the growth of digital communication, social networking websites, and web discussion forums in the recent past, sentiment analysis has become a major contender in collecting data regarding people's attitudes and trends. Nowadays, it is used widely in the fields of marketing, health care, financial institutions, and customer services to establish the sentiment of users and guide decision-making. Sentiment classification aids companies and researchers in sifting through heavy amounts of unstructured text information and extracting useful insights.

Among cat aficionados, Internet forums of controversies regarding cat breeds have been rampant. People register their opinion, experience, and concern regarding types of cats as far as temperament, health, grooming needs, and pet desirability generally. Such insight is useful for pet adoption organizations, breeders, and animal doctors in raising the level of service to the pet owners.

Sentiment analysis methods employed by supervised techniques such as Naïve Bayes, Support Vector Machines (SVM), and Logistic Regression have ever depended on. With the advent of deep learning and automatic machine learning (AutoML) algorithms, the sentiment classification process has also been highly improved and optimized. AutoML systems such as AutoGluon avoid tedious human model and hyperparameter choice by performing the above automatically.

Moreover, ensemble learning techniques have demonstrated improved predictive performance enhancement by aggregating the predictions of a collection of models. In our method, we employ a two-tier ensemble learning approach in which Naïve Bayes, SVM, and Logistic Regression are base learners and their outputs are refined by meta-learners, i.e., Random Forest, LightGBM, and Neural Networks. The hierarchical model architecture is designed to enhance the classification accuracy by aggregating the power of simple and sophisticated models.

Using ensemble learning and AutoGluon, the paper attempts to improve cat breed chat conversation sentiment classification to be correct, efficient, and applicable to web user sentiment measurement. We theorize if selection using AutoML combined with a layer-ensemble will be useful to classify. By contrasting ensemble methods to their performance by individual models, we aim to determine the optimal method through which high accuracy sentiment detection may be achieved when using domain-specific text

data. Findings in this paper contribute to growing NLP body of knowledge with evidence-based sentiment analysis methods of ensemble and AutoML methods.

With the onset of the high-speed evolution of digital communications, web communities, and social networking platforms, sentiment analysis became a sharp instrument for numerically quantifying individuals' attitude and trending emotions. Sentiment analysis is implemented in all the industries from marketing and healthcare to banking and customer relationships to determine sentiment and inform decisions. Sentiment classification facilitates corporates and researchers to parse enormous volumes of unstructured textual data and infer useful conclusions.

Within the community of cat enthusiasts, talking about cat breeds has been an online conversation subject. Individuals provide their opinions, experiences, and observations regarding various cat breeds, including their temperaments, health, grooming, and overall suitability as a companion. Having an understanding of such attitudes can assist pet adoption societies, breeders, and veterinary practitioners in refining the needs of pet owners.

Historical sentiment analysis methods are founded on supervised machine learning models such as Naïve Bayes, Support Vector Machines (SVM), and Logistic Regression. But with the advent of deep learning and access to automated machine learning (AutoML) libraries, sentiment classification has become much more effective and precise. AutoML libraries such as AutoGluon eschew the process of manually selecting models and hyperparameter tunning as they automate the entire process.

In addition, ensemble learning methods have been demonstrated to attain spectacular prediction performance improvement through predictions from model ensembles. By leveraging ensemble learning and AutoML, this study aims to make cat breed discussion sentiment classification more efficient and accurate for determining online user sentiment.

This paper investigates the application of ensemble methods of learning and AutoML for enhancing sentiment classification. Through comparison of ensemble methods and single models, we aim to set the optimal approaches for high-accuracy sentiment identification in domain text. This work's contribution further develops the emerging area of NLP by demonstrating real applications of AutoML and ensemble learning to sentiment analysis.

Since there are increasingly more people visiting web forums and social networking sites, sentiment analysis was among the key techniques for the identification of users' opinions and sentiments. Sentiment classification is applied in many fields such as marketing, medicine, and customer comments. Sentiment analysis of cat pet ownership can assist individuals in learning what individuals like and dislike about different cat breeds. Sentiment analysis of cat breed discourse is investigated in this research through the use of machine learning techniques to improve accuracy in classification.

Since tools such as AutoGluon already exist that use AutoML, it becomes simpler to select the best-performing models and hyperparameters. Ensemble learning algorithms have also succeeded in improving model accuracy using ensemble prediction by multiple classifiers. This paper aims at investigating how AutoML and ensemble learning algorithms can be used to optimize sentiment classification in cat breed controversy.

LITERATURE REVIEW

This research paper discusses sentiment analysis of cat species based on Natural Language Processing (NLP) methods. The research uses three machine learning algorithms—Naïve Bayes, Support Vector Machine (SVM), and Logistic Regression—to categorize public sentiments about different cat breeds available in online forums. The work analyzes how individuals perceive qualities such as temperament, appearance, and health of various breeds. The results show the significance of contextual information in sentiment analysis, with SVM being more accurate compared to other models. The research highlights that social networks are a rich source of public opinion, enabling sentiment analysis at a large scale on cat breeds. NLP facilitates the extraction of emotions—positive, negative, or neutral—out of large volumes of unstructured text. The research also highlights the importance of sentiment analysis in trends in pet adoption, animal welfare, and public opinion about various breeds.Future directions in this field involve increasing the granularity of sentiment classification, adding audio and image-based sentiment classification, and applying deep learning methods for higher accuracy classification. The research contributes to machine learning research and general discourse about pet culture and animal welfare [1].

This study examines the use of Automated Machine Learning (AutoML) for sentiment analysis and compares it with the conventional machine learning and deep learning techniques. AutoML is meant to make it easy to construct machine learning models through automating the model selection, hyperparameter search, and pipeline building process to minimize the expert's need for specialized knowledge. The motivation for this research is that although AutoML has the potential to drastically cut down on model development time and effort, conventional methods might still be superior in terms of performance due to manual fine-tuning and domain-specific tuning.The research employs sentiment analysis models based on different AutoML libraries, i.e., HyperOpt SkLearn, TPot, and Auto-Keras, whereas conventional models are constructed based on Scikit-learn and Keras. The study compares binary and multi-class sentiment classification models on various datasets to examine the strengths and weaknesses of each model. Through a structured comparison of the accuracy and performance of AutoML-based models and manually constructed models, the authors seek to identify if automation can match or outperform conventional methods.The findings of the research indicate that hand-crafting machine learning and deep learning models is found to be more accurate and finely optimized than models generated by AutoML. While AutoML saves a huge amount of time and brings down the barrier of entry for experts, it is not always capable of producing the best results than models developed by veteran data scientists. The study emphasizes the need for balancing machine learning with human knowledge, particularly in processes such as sentiment analysis, where thoughtful feature engineering and model choice are all-important considerations in enhancing classification performance.In the end, this research offers worthwhile insights into the strengths and weaknesses of AutoML when applied to sentiment analysis. Although AutoML tools are improving and developing continuously, conventional methods remain superior when it comes to customization and optimization of performance, and thus they are more desirable for high-precision applications [2].

Sentiment analysis is an established research discipline for retrieving sentiment-related information from data, and it has found uses in marketing, recommendation systems, and customer satisfaction analysis. Textual analysis-based approaches are based on machine learning models learned from large textual databases, but the advent of social media has seen image-based sentiment analysis as an additional means to text analysis. Multimodal sentiment analysis attempts to use text and image data to improve the accuracy of sentiment classification.Yet, current multimodal solutions are limited in their ability to integrate textual and visual information effectively because of subjectivity, inter-class homogeneity, and fusion data inconsistencies. To overcome these drawbacks, this paper introduces a new AutoML-based method that automatically determines the optimal sentiment classification model by conducting a random search across several candidate models. The new approach shows state-of-the-art performance on the B-T4SA dataset, with 95.19% accuracy. This study emphasizes the significance of multimodal data fusion in sentiment analysis and illustrates the potential of AutoML for improving model performance and selection. Future breakthroughs in the area may be able to improve real-world robustness and further fine-tune fusion methods[3].

Ensemble learning is an established method of combining several classifiers for improved model performance. Still, its adaptation to diverse and changing data, as is the case in sentiment analysis of text, has long been troublesome with changing data distribution and feature representation. Conventional ensemble methods involve a need for preexisting knowledge of the input domain to restrict applicability.In response to this, the paper proposes a reinforcement learning-based method for combining base learners in sentiment analysis. The method adaptively controls the impact of base learners in accordance with the problem space, enabling greater flexibility without prior knowledge of the data domain. This improves ensemble performance by dealing with data variability more effectively.Experimental outcomes indicate that the reinforcement learning-based integration approach is superior to classical ensemble methods, exhibiting improved accuracy and stability with respect to a range of evaluation measures. The work contributes to the research field by offering a new framework for ensemble learning, allowing more efficient processing of diverse and dynamic sentiment data[4].

The COVID-19 pandemic saw social media usage grow extensively, with a resultant vast amount of online information. This has promoted research into Natural Language Processing (NLP), here sentiment analysis, which mines emotions from text data.This research applies sentiment analysis to two data sets: coronavirus tweets and TripAdvisor hotel reviews. Two different word representation methods were used: TF-IDF (Term Frequency-Inverse Document Frequency) – frequency-based method .Word2Vec – word embedding based on prediction.For sentiment classification, the paper investigated certain machine learning and deep learning models such as:

- Standalone machine learning algorithms: Decision Trees (DT), K-Nearest Neighbors (KNN), Naïve Bayes (NB), and Support Vector Machines (SVM)

- Standalone deep learning techniques: Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN)

- Heterogeneous ensemble learning techniques: Stacking and Majority Voting

The ensemble learning method (Stacking using LSTM-RNN) performed better than all other models, with 86.4% accuracy on the COVID-19 dataset and 89.8% accuracy on the TripAdvisor dataset, showing its efficiency in sentiment analysis. The findings validate that using multiple classifiers together gives better performance, agreeing with previous studies. Investigating heterogeneous ensemble models using various algorithms in better sentiment detection is future research direction. **[5]**.

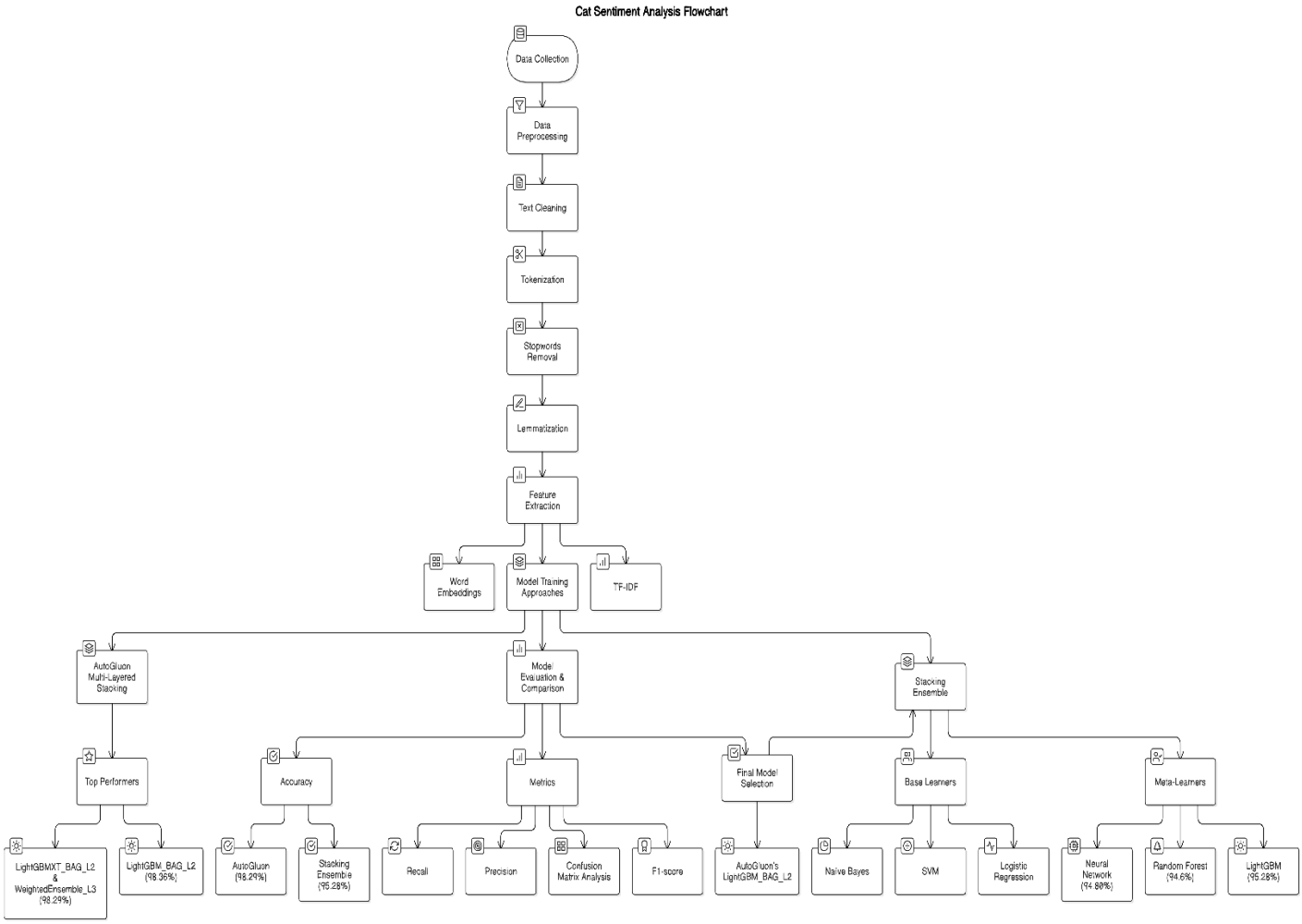
Creating Artificial Intelligence (AI) solutions is usually time-consuming and complicated, especially in Natural Language Processing (NLP). Automated Machine Learning (AutoML) can speed up the process, but it needs large-scale datasets to learn efficiently. But annotated datasets for NLP are usually costly and hard to create.To overcome this problem, the research suggests an AutoML benchmark for sentiment analysis, which comprises: 49 preprocessed datasets, More than 650 binary datasets, 204 meta-features. In addition, the research delves into Meta-Learning (MtL)—a focused AutoML method—where artificial recombination of classes is done to form new datasets. As a proof of concept, the benchmark is utilized on a hate speech detection task to illustrate the scalability and feasibility of AutoML in sentiment analysis. The research underscores the value of structured benchmarks for enhancing AutoML-based sentiment classification [6].

This study explores sentiment analysis on both handwritten and E-text statements using machine learning and deep learning techniques. The proposed ESIHE_AML model aims to detect sentiment polarity (positive, negative, neutral) and classify emotions (happiness, sadness, anger, etc.) from diverse text formats. The model demonstrates over 90% accuracy on benchmark datasets like Twitter, Kaggle, IAM, and Amazon reviews, showcasing its effectiveness in analyzing emotional content in both traditional and digital communication. The study highlights how Handwriting-to-Text Conversion (HTC), combined with advanced sentiment analysis, enhances data accessibility and emotional understanding, paving the way for future hybrid approaches to improve accuracy further [7].

This work remedies the shortcomings of Aspect-Based Sentiment Analysis (ABSA) by proposing a transfer learning-based framework that improves sentiment classification by adding multi-label classification and finer analysis of entity aspects. Most existing ABSA approaches involve large labeled data and consider sentiment classification as a single-label problem and hence do not uncover multiple sentiments corresponding to various aspects of a review.To counter these issues, the research suggests Aspect Enhanced Sentiment Analysis (AESA), which enhances sentiment classification by taking entity aspects regardless of certain

sentiments. Moreover, the research extends state-of-the-art transfer learning models to carry out multi-label ABSA and AESA tasks, enabling the model to learn from more than one domain and generalize better across various datasets.Large-scale experiments were done on data from different domains, and the outcomes indicated that the proposed method performs better than state-of-the-art ABSA techniques by enhancing sentiment classification accuracy and processing complex sentiment dependencies efficiently. This work contributes to improving sentiment analysis methods by combining transfer learning, multi-label classification, and aspect-aware sentiment assessment, which makes it a more comprehensive solution for real-world use [8].

METHODOLOGY



1. Data Collection

The dataset used for sentiment analysis of cat species is **self-made** and compiled from multiple sources to ensure diversity and completeness. Data has been gathered from the following sources:

- **Reddit API**:
  - Used **Pushshift API** or **PRAW (Python Reddit API Wrapper)** to scrape discussions and comments related to various cat breeds.
  - Extracted **post titles, descriptions, and user comments** discussing different breeds and their sentiment.
- **TheCatAPI**:
  - Retrieved **breed descriptions**, characteristics, and popularity data for different cat species.
  - Collected both textual descriptions and metadata about each breed.
- **Websites and Forums**:
  - Scraped cat-related forums and websites discussing different breeds and their characteristics.
  - Extracted **user reviews, expert opinions, and discussions** on various species.
- **Blogs and Articles**:
  - Collected content from cat-focused blogs and online articles discussing breed-specific behaviors, temperament, and user experiences.

Dataset Structure

After collection, the dataset was structured as follows:

Species	Cleaned_Title	Cleaned_Selftext
Bengal	"Bengals are playful and active"	"I love my Bengal! She is energetic and super friendly."
Persian	"Persian cats are calm and quiet"	"My Persian sleeps all day, barely plays. Is this normal?"
Sphynx	"Sphynx cats need a lot of care"	"Their skin is very sensitive, so they require special attention."

2. Data Preprocessing

Before applying machine learning models, the collected text underwent several **Natural Language Processing (NLP) steps**:

2.1 Text Cleaning

- Removed **special characters**, **HTML tags**, **punctuation**, and **URLs**.
- Converted text to **lowercase** for uniformity.
- Elimination of **stopwords** ("the", "is", "and").

2.2 Tokenization

- Split text into individual **words** or **subwords** for analysis.
- Used **NLTK and spaCy** for efficient tokenization.

2.3 Lemmatization/Stemming

- Reduced words to their **base/root** form to standardize text (e.g., "running" → "run").

2.4 Feature Extraction

To convert text into numerical form for ML models, we applied:

- **Term Frequency-Inverse Document Frequency** to illustrate word importance.

2.5 Data Splitting

- **Training Set (70%)** – Used to train the model.
- **Testing Set (20%)** – Used to evaluate model performance.
- **Validation Set (10%)** – Used for hyperparameter tuning and fine-tuning.

3. Model Training and Implementation

We implemented **two different approaches**:

3.1 Approach 1: Ensemble Learning (Stacking classifiers)

We trained multiple traditional ML models and combined them using ensemble techniques for improved accuracy.

Step 1: Train Base Models

The following models were trained on the dataset:

- **Support Vector Machine (SVM)**: Effective for text classification tasks.
- **Naïve Bayes**: A probabilistic classifier suitable for sentiment analysis.
- **Logistic Regression**: A simple yet powerful classifier for binary/multi-class classification.

Step 2: Apply Ensemble Techniques

To enhance model performance, we used **ensemble learning**:

1. **Stacking Ensemble**
    - Uses multiple base models.
    - A **meta-classifier** (Random Forest, LightGBM, Neural Networks) is trained on the outputs of the base models to improve predictions.

The meta-learners used:

- **LightGBM Meta-Learner**: Achieved an **accuracy of 95.28%**.
- **Neural Network Meta-Learner**: Achieved an **accuracy of 94.80%**.
- **Random Forest Meta-Learner**: Achieved an **accuracy of 94.60%**.

3.2 Approach 2: AutoGluon for Automated Model Selection

In addition to traditional ensemble learning, we leveraged **AutoGluon**, an automated machine learning (AutoML) framework that:

- **Automatically selects the best model** from multiple machine learning architectures.
- **Optimizes hyperparameters** using AutoML tuning.
- **Performs stacked ensembling**, combining multiple models for superior accuracy.

Key findings:

- **LightGBM_BAG_L2: Best performer with 98.36% accuracy.**
- **LightGBMXT_BAG_L2 & WeightedEnsemble_L3: Achieved 98.29% accuracy.**
- **NeuralNetFastAI_BAG_L2: Had slightly lower accuracy (96.37%) but contributed to ensemble learning.**
- **RandomForestGini_BAG_L1: Provided diverse predictions but had 93.85% accuracy.**

3.3 Model Evaluation

We used multiple evaluation metrics:

- **Accuracy**: Measures overall correctness of the model.
- **Precision**: Measures how many predicted positive instances were actually positive.
- **Recall**: Measures how well the model identifies true positives.
- **F1-Score**: Average between Precision and Recall.
- **Confusion Matrix**:Visualizes True Positives, False Positives, etc.
- **ROC-AUC Score**: The ability of the model to distinguish between classes.

The models were evaluated using standard classification metrics:

- **Accuracy**: AutoGluon (98.29%) > Stacking Ensemble (95.28%)
- **Precision, Recall, and F1-score**: Consistently high across all models, showing balanced predictions across sentiment categories.
- **Confusion Matrix Analysis**: Showed minimal misclassification, with AutoGluon outperforming the stacking ensemble.

The **best-performing approach** was selected based on these metrics.

4. Model Optimization and Hyperparameter Tuning

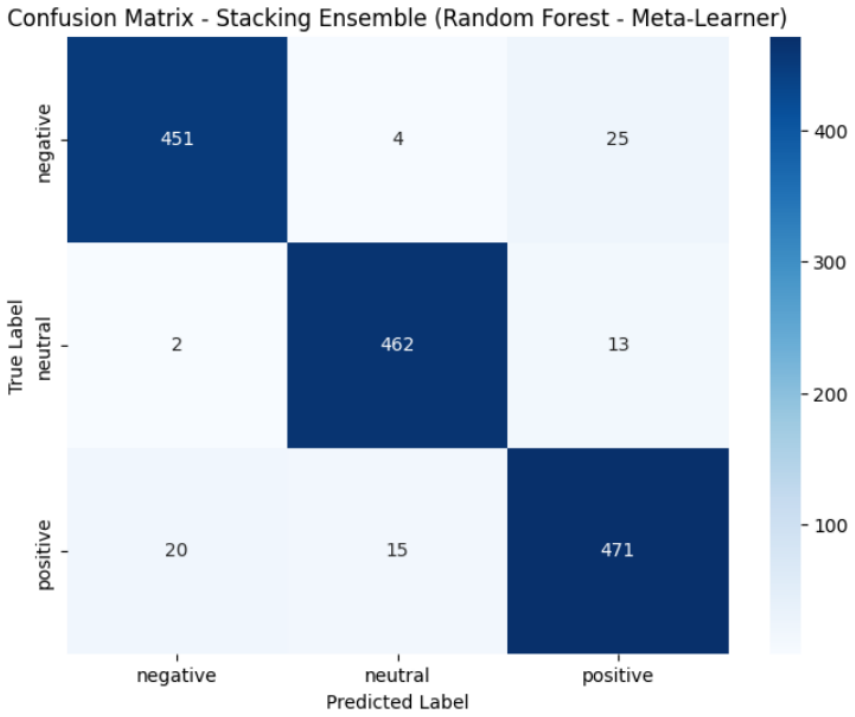
- **Traditional ML models** were optimized using **Grid Search** and **Random Search**.
- **AutoGluon** performed **automated hyperparameter tuning** without manual intervention.

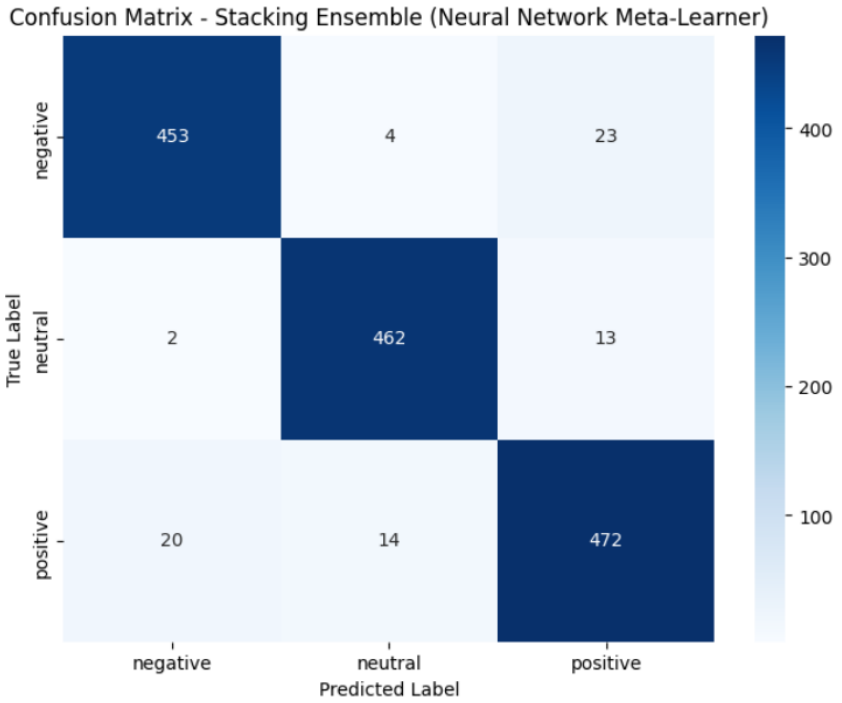
5. Final Model Selection

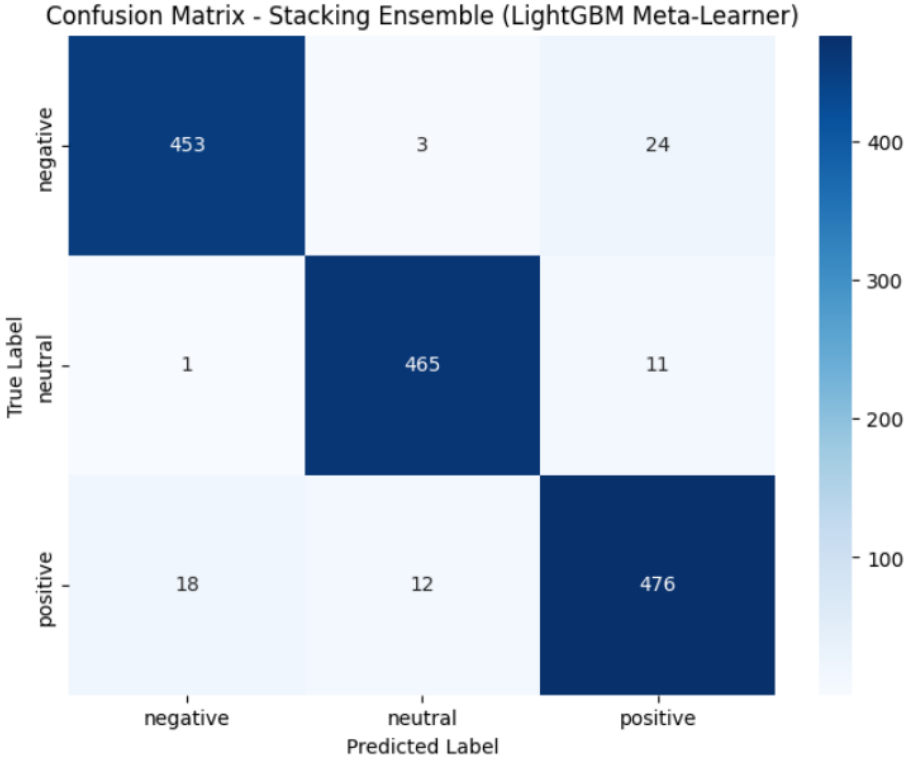
Based on performance, **AutoGluon's LightGBM_BAG_L2 was chosen as the final model** due to its superior accuracy and automated optimization capabilities. However, the Stacking Ensemble method also demonstrated strong results and remains a viable alternative for further experimentation.

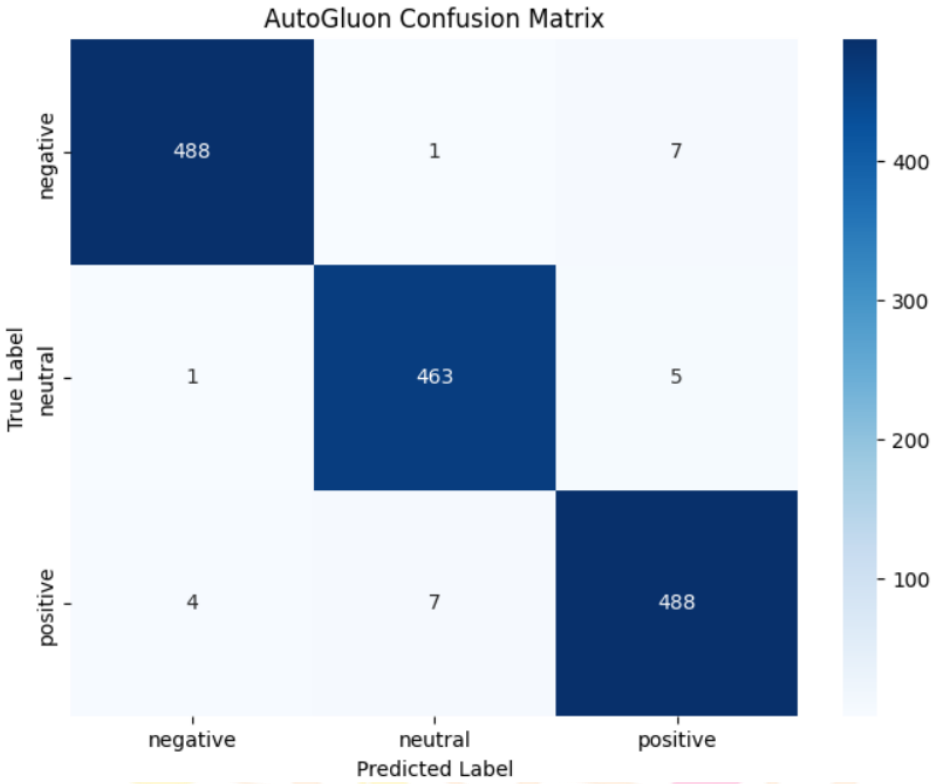
This methodology shows **both traditional machine learning (Ensemble Learning)** and **AutoGluon (AutoML)** to analyze sentiment regarding different cat species. We select the **best-performing model** for deployment, ensuring high accuracy and efficiency.

RESULTS AND OBSERVATIONS




Confusion Matrix - Stacking Ensemble (Neural Network Meta-Learner)
True Label
negative
neutral
positive
453
4
23
2
462
13
20
14
472
400
300
200
100
negative
neutral
positive
Predicted Label


Confusion Matrix - Stacking Ensemble (LightGBM Meta-Learner)
True Label
negative
neutral
positive
453
3
24
1
465
11
18
12
476
400
300
200
100
negative
neutral
positive
Predicted Label



The **Stacking Ensemble** method was implemented using multiple base learners and a meta-learner to improve performance. The results for different meta-learners were:

Meta-Learner	Accuracy (%)
LightGBM Meta-Learner	95.28
Neural Network Meta-Learner	94.80
General Stacking Ensemble	94.60

- **Precision, Recall, and F1-score** were consistently high across all sentiment categories (Negative, Neutral, Positive).
- **LightGBM performed best**, making it the most reliable choice among the meta-learners.
- **Neural Network Meta-Learner** showed slightly lower performance but still demonstrated robustness.
- **General Stacking Ensemble** had the lowest accuracy among the ensemble methods but still provided strong classification.

AutoGluon's automated model stacking achieved superior performance. The top-performing models were:

Model	Test Accuracy (%)	Validation Accuracy (%)
LightGBM_BAG_L2	98.36	97.41
LightGBMXT_BAG_L2	98.29	97.58
WeightedEnsemble_L3	98.29	97.58
NeuralNetFastAI_BAG_L2	96.37	94.12
RandomForestGini_BAG_L1	93.85	91.72

- **AutoGluon achieved the highest accuracy (98.29%)**, outperforming the Stacking Ensemble approach.
- **LightGBM_BAG_L2 was the best individual model** with a **98.36% test accuracy**.
- **Ensemble methods like WeightedEnsemble_L3 further optimized the performance** by balancing multiple models.
- **RandomForest and Neural Networks had relatively lower accuracy** but still contributed to model diversity.

CONCLUSION AND FUTURE WORK

This study explored **sentiment analysis of cat species** using **Stacking Ensemble** and **AutoGluon's Multi-Layered Stacking (AutoML)**. The results demonstrated that **AutoGluon outperformed the traditional Stacking Ensemble approach**, achieving a **higher accuracy of 98.29%**, while the best stacking ensemble model (LightGBM Meta-Learner) achieved **95.28%** accuracy.

Key takeaways from the study include:

- **LightGBM consistently delivered superior performance** across both methodologies.
- **AutoGluon's automated model selection and stacking** provided a more efficient and optimized approach to sentiment classification.
- **Stacking Ensemble remains a strong alternative**, allowing fine-grained control over model selection and tuning.
- **Feature extraction techniques such as TF-IDF and embeddings** played a critical role in text representation.

Though the present research contributes importantly to sentiment analysis based on textual data, some improvements and extensions can be undertaken:

Dataset Extension - Augment dataset size by gathering more diverse data from social media (Facebook, Instagram, Twitter), cat adoption websites, and online e-commerce reviews about cat breeds.Adding multilingual sentiment analysis to analyze sentiments in various languages.Crowdsourced annotation of data to enhance dataset quality and sentiment tagging accuracy.

Advanced Deep Learning Methods - Apply BERT-based sentiment analysis to better capture contextual and semantic text meaning.Employ LSTM and Bi-LSTM models for sequential processing of text to boost sentiment prediction.Test Transformer models such as RoBERTa, XLNet, and GPT-based models to improve further.

Multimodal Sentiment Analysis (Text + Images + Audio) - Combine image-based sentiment analysis by examining facial expressions, cat pictures, and pet-related media via Convolutional Neural Networks (CNNs).Apply multi-modal deep learning to integrate text and image data for a deeper sentiment comprehension.Investigate speech sentiment analysis for detecting emotional tones in videos or voice recordings of cat discussions.

Model Optimization & Deployment - Optimize hyperparameters with sophisticated methods such as Bayesian Optimization and Genetic Algorithms to enhance model performance.Deploy the final model as a real-time sentiment analysis API for applications such as pet adoption websites, e-commerce reviews, and social media monitoring.Create an interactive visualization dashboard to dynamically analyze sentiment trends and insights.

Explainability & Bias Mitigation - Use SHAP and LIME methods to explain model predictions and provide transparency.Mitigate bias in sentiment classification by using balanced training datasets and fairness-aware algorithms.

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