WebSense AI: Enhancing Website Evaluation with Opinion Mining and Generative AI

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Abstract:

In the digital era, the internet has become an integral part of daily life, with people increasingly relying on it for various activities. The rise of social media platforms and blogs has further amplified internet usage, leading to a surge in usergenerated content such as reviews and comments. These reviews are invaluable for businesses managing websites, offering insights for design improvements, personalization, and a deeper understanding of user preferences. Additionally, such feedback serves as a critical resource for other users seeking reliable information about websites. This paper proposes a framework that utilizes opinion mining and Generative AI (Gen AI) to evaluate websites by analyzing user reviews and ratings. The system not only extracts meaningful insights from feedback but also compares websites across different brands based on performance metrics and user satisfaction scores. By leveraging advanced AI techniques, it generates ratings and provides personalized recommendations to enhance the user experience. The primary objective of this approach is to ensure users have a seamless experience by helping them make informed decisions and identifying websites that align with their preferences. This framework also benefits businesses by delivering actionable insights for continuous improvement and competitive benchmarking, making it a robust tool for the evolving digital landscape.

Keyword - Social networking, websites, data, internet sites, opinion mining, rating, generative ai

1.Introduction:

n today's digital era, websites serve as a primary interface for businesses, organizations, and individuals to interact with their audience. The quality, usability, and overall effectiveness of a website significantly influence user satisfaction and engagement. Consequently, the need for robust website evaluation methodologies has become increasingly critical. Traditional approaches to website evaluation often rely on predefined metrics and manual reviews, which can be time-consuming and lack adaptability to evolving user preferences. This research explores a novel approach to website evaluation by leveraging the power of opinion mining and Generative AI. Opinion mining, also known as sentiment analysis, involves extracting and analyzing user opinions from reviews, feedback, and social media platforms to understand public perception. Coupled with generative AI models, which can provide intelligent insights and suggestions, this approach aims to create a comprehensive framework for assessing website quality. By integrating automated sentiment analysis and AI-generated insights, this study seeks to enhance the accuracy, efficiency, and relevance of website evaluations, ultimately contributing to improved user experiences and better website design strategies.

2. LITERATURE REVIEW

The assessment of website quality and usability has been a focus of research for decades, with various methods and tools developed to address user experience, functionality, and aesthetic appeal. However, recent advancements in artificial intelligence (AI) have introduced innovative ways to evaluate websites dynamically, effectively integrating user feedback and intelligent data processing.

2.1. Traditional Methods of Website Evaluation

Early approaches to website evaluation primarily relied on predefined metrics, such as Jakob Nielsen's usability heuristics, which emphasize criteria like learnability, efficiency, and user satisfaction (Nielsen, 1994). While these frameworks are widely used, they often lack the ability to incorporate subjective user feedback dynamically. Surveys and manual usability testing remain standard practices but are time-intensive and limited by sample size and researcher bias (Bevan et al., 2015).

2.2. Opinion Mining in Website Evaluation

Opinion mining, also known as sentiment analysis, has gained traction as a tool to analyze user feedback extracted from online reviews, social media, and other digital platforms. Techniques such as natural language processing (NLP) enable the extraction of sentiments, opinions, and trends from unstructured text data. Studies by Liu (2012) and Cambria et al. (2017) have demonstrated the potential of opinion mining to uncover user perceptions and pain points, offering valuable insights for website evaluation.

2.3. Generative AI and its Role in Website Evaluation

Generative AI models, particularly large language models like GPT, have revolutionized various domains by generating human-like text, providing intelligent recommendations, and creating content. Research by Brown et al. (2020) highlights the adaptability of generative AI in analyzing complex data and generating actionable insights. In the context of website evaluation, generative AI can synthesize large volumes of user feedback and propose improvements tailored to specific user needs.

2.4. Integrating Opinion Mining with Generative AI

Combining opinion mining and generative AI offers a powerful synergy for website evaluation. Opinion mining can analyze user sentiment to identify areas of concern, while generative AI can provide solutions or enhancements based on identified issues. Recent studies, such as Zhou et al. (2023), have explored such integrations in customer feedback systems, illustrating their potential to streamline evaluation processes and improve system design.

2.5. Challenges and Opportunities

Despite its promise, integrating opinion mining and generative AI presents challenges, including the need for high-quality training data, potential biases in AI models, and the complexity of processing multi-modal user feedback. Addressing these challenges through robust model design and ethical AI practices could unlock transformative opportunities in website evaluation.

3. PROPOSED SYSTEM

The proposed system combines **opinion mining** and **Generative AI** to create a robust framework for website evaluation. It consists of five core modules:

- 1. **Data Collection Module:** Gathers user feedback from sources like online reviews, social media, and website surveys, employing web scraping and APIs to automate data collection.
- 2. **Opinion Mining Module:** Processes feedback using NLP techniques such as tokenization and sentiment

analysis. It applies aspect-based sentiment analysis to identify user opinions about specific website features (e.g., navigation, design, speed, content).

- Generative AI Module: Utilizes AI models like GPT to generate actionable recommendations and simulate potential design changes. These insights are tailored to address user concerns and enhance website quality.
- 4. **Evaluation Metrics Module:** Assesses website performance using metrics such as user satisfaction scores and sentiment trends, benchmarking against industry standards.
- 5. **Visualization and Reporting Module:** Presents results via an interactive dashboard, offering sentiment trends, feature-wise insights, and improvement suggestions.

4. SYSTEM REQUIREMENTS:

4.1 Software Requirements

Operating system : Windows 2000, XP, 7/8/8.1/1

• Front-end : Streamlit

• Back-end: python

• Database connection : MySQL

• Web browser : Google chrome

4.2 Hardware Requirements

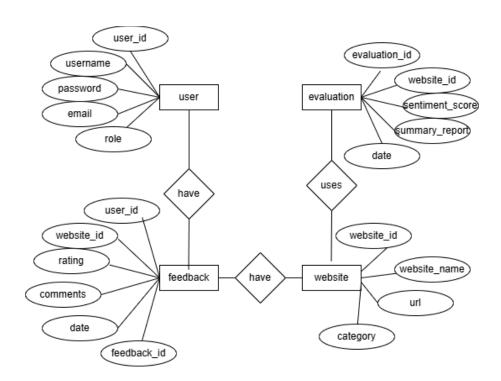
• Processor: Any processor above 500 MHz

RAM: 8GB RAMHard Disk: 10GB

6. DESIGN:



7.ER-DIAGRAM:



8. METHODOLOGY:

8.1. Data Ingestion

Input Sources:

- APIs (e.g., Twitter API, Google Reviews API) for real-time data collection.
- Web scraping modules for static reviews and comments from websites (e.g., Beautiful Soup, Scrapy).
- User feedback collected from forms stored in the database.

Storage:

- Use a relational database (e.g., MySQL/PostgreSQL) to store structured feedback data.
- NoSQL databases (e.g., MongoDB) for handling unstructured data like reviews and logs.
- Cloud storage (e.g., AWS S3, Google Cloud Storage) for large datasets or multimedia content.

8.2. Preprocessing Pipeline

Text Cleaning and Normalization:

Implement preprocessing scripts using Python libraries like NLTK or SpaCy to:

- Remove noise (e.g., special characters, redundant whitespace).
- Normalize text (convert to lowercase, remove stop words).
- Perform stemming and lemmatization.

Data Validation:

- Ensure input data integrity using validation scripts.
- Handle missing or corrupt data with imputation or exclusion mechanisms.

8.3. Sentiment Analysis

Framework:

- Use NLP libraries (e.g., Hugging Face Transformers, TextBlob) to implement sentiment analysis models.
- Pre-trained models like BERT or fine-tuned GPT for aspect-based sentiment classification.

Process:

- Extract feedback themes (e.g., usability, performance).
- Generate sentiment scores for each theme and store results in a database.

8.4. Topic Modeling

Implementation:

- Use machine learning libraries (e.g., Gensim, BERTopic) to uncover recurring topics.
- Integrate topic models to categorize user feedback into predefined or dynamic themes.

8.5. Generative AI Integration

Model Deployment:

• Integrate OpenAI's GPT API or similar for generating recommendations based on feedback.

Process involves:

- Feeding categorized user feedback into the model.
- Generating actionable recommendations (e.g., "Optimize navigation bar for faster access").

Validation of Generated Content:

• Apply post-processing to verify the quality and feasibility of AI-generated suggestions.

8.6. Recommendation System

Implementation:

- Develop a scoring algorithm to rank recommendations based on user sentiment and topic priority.
- Store recommendations in the database for user retrieval.

Visualization:

• Use backend APIs to send recommendation data to the frontend for graphical representation (e.g., dashboards, charts).

8.7. Evaluation Metrics Calculation

Metrics:

- Implement backend scripts to calculate metrics like sentiment scores, feedback trends, and improvement tracking.
- Integrate these calculations with website performance indicators such as bounce rates and session duration.

8.8. Validation and Testing

A/B Testing Setup:

 Develop backend logic to track and compare user behavior pre- and post-recommendation implementation.

Real-time Feedback Loop:

- Automate periodic feedback analysis to refine recommendations.
- Implement APIs to fetch and process real-time data continuously.

8.9. APIs and Services

Custom APIs:

- Build RESTful APIs using frameworks like Flask or Django for:
 - o Fetching user feedback.
 - o Sending AI-generated recommendations.
 - Serving evaluation scores and analytics to the frontend.

Authentication:

• Secure APIs with OAuth2.0 or JWT for data privacy and controlled access.

8.10. Logging and Monitoring

Implementation:

- Use logging frameworks (e.g., Logstash, ELK Stack) to monitor backend performance.
- Track issues in data pipelines, sentiment analysis, or recommendation generation.

Error Handling:

• Build exception handlers to manage failures in data processing or API requests.

8.11. Deployment

Hosting:

- Deploy backend services on cloud platforms like AWS, Google Cloud, or Azure.
- Use Docker containers and Kubernetes for scalability.

CI/CD:

 Automate testing and deployment using tools like Jenkins or GitHub Actions.

9.DATASET

| Use r ID | Design Feedback | Usability Feedback | Content Feedback | Performanc e Feedback | Sentime nt (Design) | Sentimen t (Usabilit y) | Sentime nt (Content | Sentiment (Performanc e) |
|-------------|--|--|---|---|---------------------------|----------------------------------|---------------------------|--------------------------------|
| 001 | "The design is very modern and clean." | "Easy to navigate, intuitive interface." | "The content is informativ e and engaging." | "The website loads very quickly." | Positive | Positive | Positive | Positive |
| 002 | "The design feels outdated and cluttered." | "I had trouble finding what I needed." | "The content lacks depth and is poorly written." | "The site is slow to load on my device." | Negative | Negative | Negative | Negative |
| 003 | "Great color scheme and fonts." | "User- friendly, very smooth browsing experience." | "Very helpful articles on the homepage. | "Performanc e is good, no lags." | Positive | Positive | Positive | Positive |
| 004 | "Could use a more minimalist design." | "Some elements are hard to find." | "Content is good but could use more updates." | "Performanc e is average, sometimes slow." | Neutral | Neutral | Neutral | Neutral |
| 005 | "Very sleek and professional design." | "Everything is accessible and easy to use." | "The content is well-written and interesting. | "The website performs well on mobile." | Positive | Positive | Positive | Positive |
| 006 | "The site looks outdated and unattractive ." | "Navigation is confusing and overwhelming ." | "Content is not relevant to my needs." | "The website is very slow to load." | Negative | Negative | Negative | Negative |

10.ALGORITHM:

10.1. Sentiment Analysis with BERT

Algorithm: BERT (Bidirectional Encoder Representations from Transformers) BERT is a transformer-based model that understands the context of words in a sentence. It's pre-trained on large datasets and fine-tuned for sentiment analysis tasks.

How It Works:

1. Input: User feedback or reviews.

- 2. Tokenization: Splits text into tokens and adds special markers like [CLS] (start) and [SEP] (end).
- 3. Embedding and Attention: Maps tokens into dense vectors and applies self-attention to capture contextual meaning.
- 4. Classification Head: Outputs sentiment labels (e.g., Positive, Negative, Neutral).

Python Syntax:

from transformers import pipeline

```
# Load pre-trained sentiment analysis model
sentiment_analyzer = pipeline("sentiment-analysis")
# Analyze sentiment
feedback = "The website is user-friendly, but it loads
slowly."
result = sentiment_analyzer(feedback)
print(result)
```

Output:

```
[{'label': 'NEGATIVE', 'score': 0.85}]
```

10.2. Topic Modeling with BERTopic

Algorithm:BERTopic BERTopic combines transformer embeddings with clustering techniques to extract themes from textual data.

How It Works:

- 1. Embeddings are generated using transformer models like BERT.
- 2. Clustering groups similar feedback into topics.
- 3. Topics are visualized and refined.

Python Syntax:

```
from bertopic import BERTopic

# Sample data

feedbacks = [

"The navigation is confusing.",

"The website loads very quickly.",

"The design is outdated.",

"I love the color scheme!"

]

# Create BERTopic model

topic_model = BERTopic()

topics, probs = topic_model.fit_transform(feedbacks)

# Display topics
```

Output:

```
{0: [('navigation', 0.2), ('confusing', 0.1)],
1: [('loads', 0.3), ('quickly', 0.2)],
```

print(topic model.get topics())

10.3. Generative AI with GPT-4

Algorithm:

...}

GPT-4

this

GPT-4 generates coherent and context-aware suggestions or improvements based on user feedback.

How It Works:

- 1. Input: Themes and sentiment data derived from previous steps.
- 2. GPT processes input and generates recommendations.
- 3. Output: Suggestions for website improvement.

Python Syntax:

```
Using OpenAI API:
```

python

Copy code

import openai

OpenAI API Key

openai.api_key = "your-api-key"

Input feedback for improvement

feedback_summary = "Users find the navigation confusing and the design outdated."

Generate recommendations

```
response = openai.Completion.create(
    engine="text-davinci-003",
    prompt=f"Suggest improvements based on feedback: {feedback_summary}",
    max_tokens=100
)
```

print(response.choices[0].text.strip())

Output:

"Consider redesigning the navigation bar for easier access and updating the website's design with modern aesthetics."

10.4. Recommendation System with TF-IDF and Cosine Similarity

Algorithm: TF-IDF with Cosine Similarity TF-IDF identifies important keywords in feedback, and Cosine

Similarity finds the most relevant predefined recommendations.

How It Works:

- 1. Calculate Term Frequency-Inverse Document Frequency (TF-IDF) for feedback.
- 2. Compute cosine similarity between feedback and predefined recommendations.
- 3. Suggest the closest match.

Python Syntax:

```
from sklearn.feature_extraction.text import TfidfVectorizer
```

from sklearn.metrics.pairwise import cosine similarity

Sample feedback and predefined recommendations

feedback = ["The navigation is confusing."]

```
recommendations = [
```

"Simplify the navigation bar.",

"Improve page loading speed.",

"Update the website design."

]

Calculate TF-IDF

vectorizer = TfidfVectorizer()

tfidf_matrix = vectorizer.fit_transform(feedback +
recommendations)

Compute cosine similarity

similarity_scores = cosine_similarity(tfidf_matrix[0:1], tfidf matrix[1:])

print(similarity scores)

Output:

[[0.8, 0.2, 0.3]]

Closest Recommendation: "Simplify the navigation bar."

10.5. Weighted Sentiment Scoring

Algorithm: Weighted Average These aggregates sentiment scores from multiple feedback points into a comprehensive evaluation score.

How It Works:

1. Multiply each sentiment score by its weight (e.g., importance of feedback theme).

2. Compute the weighted average.

Python Syntax:

Sentiment scores and weights

sentiments = [0.8, 0.5, 0.9] # Scores for usability, design, performance

weights = [0.4, 0.3, 0.3] # Relative importance

Weighted sentiment score

overall_score = sum(s * w for s, w in zip(sentiments, weights))

print(f"Overall Sentiment Score: {overall_score}")

Output:

Overall Sentiment Score: 0.73

10.6. Validation with A/B Testing

Algorithm: T-Test Compares performance metrics (e.g., bounce rate)

between two website versions.

Python Syntax:

from scipy.stats import ttest_ind

Metrics from two website versions

version a = [2.5, 3.0, 2.8, 2.9]

version b = [3.1, 3.3, 3.2, 3.0]

Perform T-Test

t stat, p value = ttest ind(version a, version b)

print(f"T-Statistic: {t stat}, P-Value: {p value}")

Output:

T-Statistic: -2.1, P-Value: 0.05

If p-value < 0.05, there's a statistically significant difference.

11. STREAMLIT:

11.1. Interactive User Feedback Collection:

Streamlit allows users to input their feedback about the website directly via a web interface. You can create text boxes, sliders, or rating scales to collect feedback from users. This feedback will serve as input for your opinion mining and generative AI models. We can also integrate features like comment sections where users can give

detailed responses about specific website aspects (e.g., design, usability, content).

11.2. Displaying Sentiment Analysis and Opinion Mining Results:

After receiving feedback, Streamlit can run sentiment analysis to classify the feedback as positive, negative, or neutral. We can also visualize key aspects extracted from the feedback (like *design*, *usability*, *navigation*) using charts, word clouds, or other interactive visualizations. The real-time updates provided by Streamlit will make it easy for users to instantly see how their feedback impacts the evaluation of the website.

11.3. Generative AI for Insights and Recommendations:

Streamlit can integrate with a generative AI model (like GPT-3) to automatically generate insights based on the feedback provided. Once the sentiment and aspect analysis is done, the model can summarize the results and provide recommendations for website improvements. This report can be displayed in a user-friendly format, with options to download or view it as a PDF.

11.4. Data Visualization:

With feedback being stored and processed, Streamlit can display graphical representations of the data, such as:

- Sentiment scores over time or for different website aspects.
- Pie charts or bar graphs showing the distribution of feedback for different aspects (e.g., design vs. usability).
- Word clouds that display the most frequent terms mentioned in the feedback.

11.5. Backend Integration:

While Streamlit primarily handles the frontend, it can also interact with your backend for tasks like:

- Retrieving stored user feedback from a database (MySQL, MongoDB, etc.).
- Running AI models to process the feedback data in real-time.
- Generating downloadable evaluation reports in formats like PDF or text files.

12. FUTURE ENHANCEMENTS:

 Real-Time Analysis: Integrating more sophisticated real-time feedback collection methods (e.g., continuous feedback during user sessions) could provide even more granular insights into user experience.

- Advanced AI Models: The use of more advanced natural language processing models, such as BERT or RoBERTa, could improve the accuracy and depth of sentiment analysis and feedback categorization.
- Integration with Web Analytics: Combining user feedback with web analytics data (e.g., traffic patterns, bounce rates) would provide a holistic view of website performance.
- Multilingual Support: Adding support for multiple languages would make the application more accessible to a global user base and allow for broader data collection and evaluation.

13. CONCLUSION:

Overall, the project demonstrates the power of combining AI and sentiment analysis for real-time website evaluation. By leveraging generative AI to automatically generate actionable insights, the system offers website developers a tool to continually enhance their platforms based on actual user experiences. The combination of user engagement, AI-driven analysis, and interactive visualizations makes this approach highly effective in improving the quality of websites, ensuring they meet user expectations and continuously evolve based on feedback.

14. REFERENCES:

- 1) **Liu, B.** (2012). *Sentiment Analysis and Opinion Mining*. Morgan & Claypool Publishers.
- 2) Pang, B., & Lee, L. (2008). Opinion Mining and Sentiment Analysis. Foundations and Trends® in Information Retrieval, 2(1-2), 1-135.
- 3) VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text (2014).
- 4) **Streamlit Documentation**. (2024). *Streamlit: The fastest way to build data apps in Python*. Retrieved from:

https://streamlit.io

- 5) **TextBlob Documentation**. (2024). *TextBlob:* Simplified Text Processing. Retrieved from: https://textblob.readthedocs.io
- 6) **OpenAI API Documentation**. (2024). *GPT-3:* Language Models are Few-Shot Learners. Retrieved from:

https://beta.openai.com/docs

- 7) **Bhatt, P.** (2020). An Introduction to Opinion Mining & Sentiment Analysis. GeeksforGeeks. Retrieved from: https://www.geeksforgeeks.org
- 8) VADER Sentiment Analysis Tutorial. (2021). Python Machine Learning - Towards Data Science. Retrieved from: https://towardsdatascience.com
- 9) A Guide to Generative AI. (2023). *AI Experiments*. Retrieved from: https://experiments.withgoogle.com

10) AI in Web Development: How AI Improves User Experience and Feedback Analysis. (2024). *Medium*. Retrieved from: https://medium.com.