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Mood-Based Song Recommendation System Using Sugeno Fuzzy Logic

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ABSTRACT
Digital music platforms expose listeners to large catalogs, making mood-oriented filtering useful for music discovery. This study built a content-based song recommender that maps Spotify audio features to five mood levels using zero-order Sugeno fuzzy logic. The model uses valence, energy, tempo, and mode from SpotifyFeatures.csv. Triangular membership functions activate five rules whose consequents represent very sad, sad, neutral, happy, and very happy. The resulting mood score is used for both classification and ranking songs by distance from a selected mood target. The prototype combines a FastAPI backend and a React interface for recommendation and song search. The work provides an auditable baseline; validation with listener judgments remains necessary.

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INTRODUCTION

Digital music services have changed music listening from manual collection browsing into large-scale catalog exploration. Users can access hundreds of thousands or millions of tracks, yet the practical value of this access depends on how effectively the system can filter songs according to a listener's current context. Mood is one of the most intuitive contexts in music discovery because users often describe listening needs through affective states rather than through technical audio properties. A recommendation model that can translate audio features into interpretable mood categories is therefore useful for improving search, playlist construction, and casual discovery.

Music recommender systems have developed from simple popularity-based ranking into content-based, collaborative, hybrid, and emotion-aware approaches. Recent survey literature shows that music recommendation research increasingly considers audio features, contextual signals, user behavior, affective interpretation, and listening context rather than treating songs only as neutral catalog items (Amiri et al., 2024; Han et al., 2022). Content-based classification and recommendation networks also show that audio features remain useful when user history is limited (Mao et al., 2022). Emotion-aware models can improve relevance because affect is closely related to how users select music for relaxation, motivation, concentration, or emotional regulation (Han et al., 2022; Jing et al., 2025). However, many high-performing approaches rely on complex machine learning architectures that are difficult to explain to non-technical users and are not always suitable for small applied systems.

Fuzzy-set theory is appropriate for this problem because mood categories have soft boundaries. A track with moderate valence, medium energy, and a major mode does not belong cleanly to one affective class. Fuzzy membership degrees represent this graded relation , while Sugeno inference converts activated rules into a crisp score that can be ranked and displayed (Lu et al., 2024; Takagi & Sugeno, 1985).

The method fits this prototype because the rule base is readable, the output is numeric, and the computation is simple enough for a web service. The prototype uses SpotifyFeatures.csv as the content source and processes four audio variables: valence, energy, tempo, and mode. Valence approximates musical positivity, energy describes intensity, tempo captures speed, and mode indicates major or minor tonality. The model does not infer the psychological state of a listener. It estimates the dominant mood tendency of each song and ranks songs by closeness to a selected target mood.

The contribution is a working five-level Sugeno fuzzy recommender connected to a web interface. The work is applied rather than algorithmically novel: it documents the rule base, converts audio features into mood scores, and uses those scores for recommendation ranking in a FastAPI and React architecture. The research question is: how can Sugeno fuzzy logic be implemented to classify and recommend songs based on mood-related Spotify audio features?

LITERATURE REVIEW

Music Recommendation and Emotion-Aware Filtering

A recommender system predicts or ranks items that are likely to be relevant to users. In the music domain, recommendations can be generated from listening history, user similarity, item similarity, audio content, contextual factors, or hybrid combinations of these signals. Content-based music recommendation is especially useful when user profiles are unavailable because the system can operate directly on song attributes. This reduces dependence on user interaction history and can mitigate a cold-start problem for listeners who have not yet provided enough behavioral data.

Emotion-aware music recommendation extends conventional recommendation by considering affective qualities and listening context. Studies on music emotion recognition show that musical affect can be estimated from acoustic properties, lyrics, tags, and user responses (Gomez-Canon et al., 2023; Han et al., 2022). Audio-feature surveys further support the use of measurable signal descriptors for music emotion recognition tasks (Panda et al., 2023). Deep learning approaches can model complex patterns in audio representations and have advanced the state of the art in music signal processing (Moysis et al., 2023). Nevertheless, applied systems often face tradeoffs between accuracy, explainability, available data, and implementation complexity. For a transparent prototype, a rule-based fuzzy model can be appropriate because the contribution of each variable can be inspected directly.

Prior work also indicates that emotion-aware music recommendation is not only a classification problem. It is also a ranking problem because users often request a mood target and expect several suitable songs rather than a single label. (Tran et al., 2024) emphasize that emotion-aware recommendation should connect recognition output with recommendation utility, while (Melchiorre et al., 2023) show that affective interfaces can support music discovery and recommendation. In this study, the Sugeno output is used for both mood prediction and ranking. Songs are ranked according to their distance from a target mood score, which makes the link between classification and recommendation explicit.

Spotify Audio Features

The dataset used in this study is SpotifyFeatures.csv from Kaggle (Hamidani, 2019). It contains 232,725 song records and 18 columns, including genre, artist name, track name, popularity, acousticness, danceability, duration, energy, instrumentalness, key, liveness, loudness, mode, speechiness, tempo, time signature, and valence. The implementation uses four input variables: valence, energy, tempo, and mode. These variables are sufficient for a compact fuzzy model because each has a clear relation to mood interpretation and can be represented with simple membership functions.

Valence is interpreted as the degree of positive musical affect. Higher valence is associated with brighter and more positive musical impressions, while lower valence is associated with darker or sadder impressions. Energy captures intensity and activity, while tempo describes beats per minute and helps distinguish slow, moderate, and fast songs. These audio descriptors are commonly discussed as measurable inputs for music emotion recognition, although they do not fully determine subjective perception (Han et al., 2022; Panda et al., 2023). Mode is represented as a binary feature in the dataset, where major is encoded as 1 and minor as 0 in the system. Major mode is generally associated with brighter affect, while minor mode tends to support sadder interpretation, although this relation is not universal and should be treated as a supporting signal rather than a complete determinant (Gomez-Canon et al., 2023).

Fuzzy Logic and Sugeno Inference

Classical sets treat membership as binary. Fuzzy sets instead assign each input a degree of membership between 0 and 1, allowing one song to partially match more than one mood category (Zadeh, 1965). Membership functions formalize this relation between numerical features and linguistic labels. The model uses triangular membership functions because their parameters are easy to inspect, easy to reproduce, and sufficient for a compact rule-based prototype (Pedrycz, 1994).

Sugeno inference combines fuzzy antecedents with crisp consequents. In this study, each rule has a zero-order consequent, so the rule returns a constant mood score rather than a learned function. This design follows the Takagi, Sugeno, and Kang fuzzy model family for systems that require a crisp output from fuzzy rules (Sugeno & Kang, 1988; Takagi & Sugeno, 1985). The backend computes rule activation with the minimum operator and returns a neutral score of 3.0 when no rule is activated.

Recent fuzzy machine-learning literature places interpretability and uncertainty representation at the center of fuzzy-system use (Lu et al., 2024). Music recommendation studies have also used fuzzy logic to connect ambiguous affective interpretation with rule-based recommendation (Aldeshev et al., 2025; Pandey, 2025). The present work follows that applied direction and limits its claim to implementation and traceability, not optimization.

METHODOLOGY

Research Design

The study follows an applied quantitative design. The object is Spotipy, a web-based song recommendation prototype. The system reads numerical audio features from SpotifyFeatures.csv and maps them to five mood scores through Sugeno fuzzy logic. The research stages were dataset preparation, feature selection, fuzzy domain definition, membership-function design, rule construction, implementation, and functional testing of recommendation and search outputs.

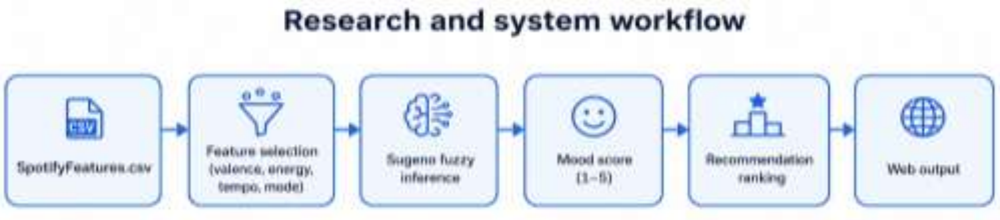

Figure 1. Research and System Workflow

Dataset and Variables

The dataset contains 232,725 song records. The columns used by the fuzzy model are valence, energy, tempo, and mode. Track name, artist name, and genre are retained for display in the web interface. Tempo values are clipped into the fuzzy domain of 50 to 200 beats per minute because extreme values outside this range can distort membership interpretation. Mode is converted into a numerical variable, with minor represented as 0 and major as 1.

Table 1. Summarizes The Primary Fuzzy Inputs.

Variable	Domain	Role in the model
Valence	0.00-1.00	Represents the positive or negative musical tendency.
Energy	0.00-1.00	Represents intensity and activity level.
Tempo	50-200 BPM	Represents slow, moderate, or fast rhythm.
Mode	0 or 1	Represents minor or major tonal mode.

Sugeno Rule Design

The deployed backend defines five target moods with Indonesian API labels: sangat sedih, sedih, netral, bahagia, and sangat bahagia. The manuscript reports these labels in English as very sad, sad, neutral, happy, and very happy. Each mood is mapped to an ordinal Sugeno consequent from 1 to 5. These values are not psychological measurements; they are anchors for ranking songs by distance from a selected mood target.

Table 2. Fuzzy Rule Structure

Mood	Valence	Energy	Tempo	Mode	z
Very sad	[0.00, 0.00, 0.25]	[0.00, 0.00, 0.35]	[50, 50, 80]	Minor	1
Sad	[0.00, 0.25, 0.50]	[0.00, 0.30, 0.60]	[60, 85, 115]	Minor	2
Neutral	[0.35, 0.50, 0.65]	[0.35, 0.50, 0.65]	[90, 120, 150]	Major or minor	3
Happy	[0.50, 0.70, 0.90]	[0.40, 0.65, 0.90]	[100, 130, 170]	Major	4
Very happy	[0.75, 1.00, 1.00]	[0.65, 1.00, 1.00]	[130, 170, 200]	Major	5

The membership functions for continuous inputs are shown in Figure 2. The curves reflect the actual valence, energy, and tempo parameters implemented in the backend code. Mode is binary and is therefore represented separately in the rule formulas rather than plotted as a continuous curve.

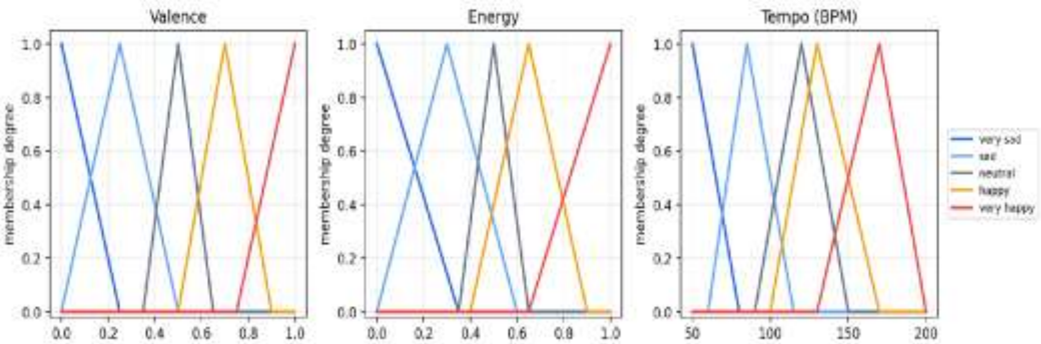

Figure 2. Sugeno Membership Functions For Valence, Energy, and Tempo

Each song is represented by an input vector x = (v, e, t, m), where v is valence, e is energy, t is tempo, and m is mode. The triangular membership function used for valence, energy, and tempo is defined as follows:

$$\mu A(x;\ a,b,c)\ =\ max\{min\left[\frac{x\ -\ a}{b\ -\ a},\frac{c\ -\ x}{c\ -\ b}\right],0\} \quad (1)$$

In the implemented shoulder cases, very low and very high categories use a = b or b = c, following the trimf behavior used in the notebook and backend. The binary mode membership is defined as follows:

$$\mu_{minor}(m)=1 \text{ if } m=0, \text{ otherwise } 0;\ \ \mu_{major}(m)=1 \text{ if } m=1, \text{ otherwise } 0;\ \ \mu_{neutral\_mode}(m)=1 \quad (2)$$

For each rule i, the firing strength is calculated as the minimum membership degree among valence, energy, tempo, and mode:

$$w_i = \min\{\mu_{Vi}(v), \mu_{Ei}(e), \mu_{Ti}(t), \mu_{Mi}(m)\} \quad (3)$$

The zero-order Sugeno output is then calculated using the weighted average of the rule consequents:

$$y\ =\ \frac{[\Sigma i\ wizi]}{[\Sigma i\ wi]};\ \ y\ =\ 3.0\ when\ \Sigma i\ wi\ =\ 0 \quad (4)$$

where w_i is the firing strength of rule i and z_i is the corresponding mood consequent. The backend function interpretasi_sugeno_output applies the following five-class threshold logic:

label(y): y < 1.5 very sad; 1.5 ≤ y < 2.5 sad
2.5 ≤ y < 3.5 neutral; 3.5 ≤ y < 4.5 happy; y ≥ 4.5 very happy (5)

For recommendation, each song output y_j is compared with the selected target mood score z_target. The distance and display score are calculated as follows:

$$d_j = |y_j - z_{target}| \quad (6)$$

$$score_j = clip(1 - d_j/4, 0, 1) \quad (7)$$

Songs are ranked by ascending d_j and then by Sugeno output, while duplicate track-artist pairs are removed before the top results are returned.

System Architecture

The system is implemented with a FastAPI backend and a React frontend. The backend loads SpotifyFeatures.csv, converts mode into a numerical variable, computes Sugeno output for songs, and exposes three main endpoints: /api/moods, /api/recommend, and /api/search. The /api/moods endpoint returns the five Indonesian backend labels used by the application: sangat sedih, sedih, netral, bahagia, and sangat bahagia. The recommendation endpoint accepts one of these target mood labels and a count, computes the Sugeno output for candidate songs, measures distance from the target score, and returns the closest songs after removing duplicate track-artist pairs. The search endpoint accepts a query string and returns matching songs with their predicted mood.

The frontend provides two workflows. The first workflow allows users to select a mood and the number of songs to display. The second workflow allows users to search for a song title and view the predicted dominant mood. Each result includes track name, artist name, genre, Sugeno output, and a generated YouTube search link. This architecture keeps the inference logic in the backend while using the frontend for interaction and presentation.

RESEARCH RESULT

Functional Implementation

The implementation loads the dataset, applies membership functions, calculates rule firing strengths, and returns JSON responses for recommendation and search requests. The frontend reads these responses and displays ranked songs. Functional testing confirmed that the application returns mood recommendations, handles search queries, and reports the Sugeno score associated with each result.

Table 3 presents an example of dataset records used by the system. The values show how valence, energy, tempo, and mode can differ across tracks and therefore activate different fuzzy rules.

Table 3. Dataset Record

No.	Track	Valence	Energy	Tempo	Mode
1	Sanctuary	0.316	0.650	167.788	Major
2	My Mistake	0.541	0.704	97.075	Major
3	Peace Sign	0.618	0.935	100.003	Minor
4	The Night We Met	0.105	0.379	174.118	Major
5	Seven Nation Army	0.324	0.463	123.881	Major

Recommendation Output

The recommendation process maps the selected target mood to a numerical score: very sad to 1, sad to 2, neutral to 3, happy to 4, and very happy to 5. The backend then calculates the absolute distance between each song output and the target. The displayed recommendation score is one minus the normalized distance, with distance divided by 4 and the result clipped to the interval from 0 to 1. Songs with smaller distance values are ranked higher.

The ranking rule is auditable. A happy request is matched against the target score 4, while a neutral request is matched against 3. Songs with lower absolute distance from the target score appear earlier in the list. This design links the predicted label and the recommendation order through the same Sugeno output.

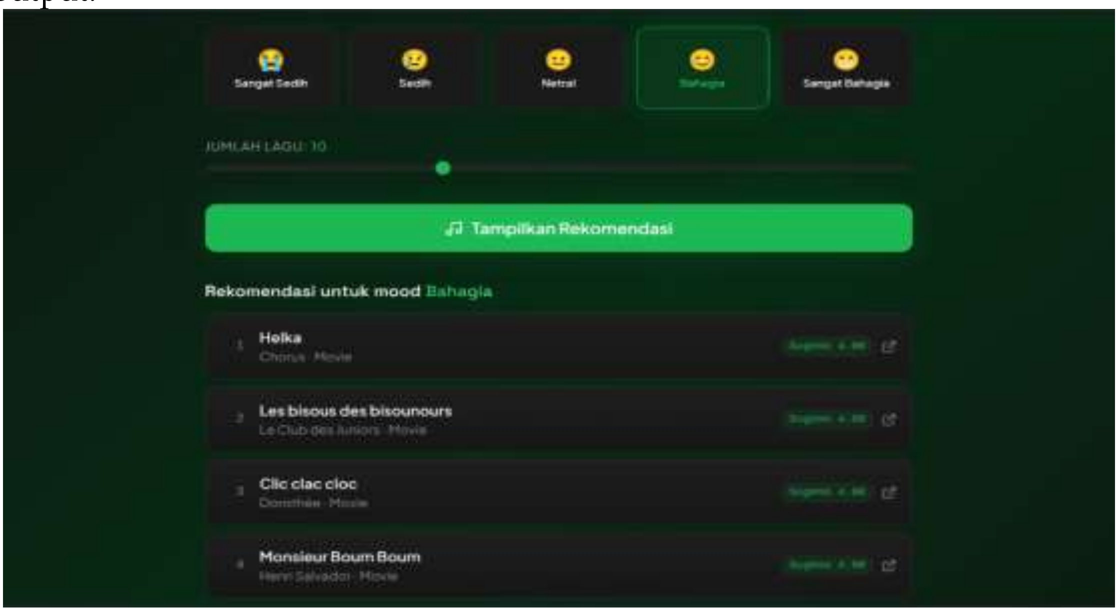

Figure 3. Happy Mood Output

Search and Mood Prediction Output

The search workflow allows users to input a song title or partial title. The backend searches the lowercased track-name column and computes Sugeno output for matching records. Results are sorted and limited by count. This feature complements direct recommendation because it allows users to inspect the predicted mood of songs they already know.

The functional result answers the research question at prototype level. Sugeno fuzzy logic can transform selected Spotify audio features into a five-level mood output and reuse that output for recommendation ranking. The implementation also shows that a rule-based model can be connected to a modern web stack without model training or manually labeled mood annotations.

DISCUSSION

The results demonstrate the practical value of Sugeno fuzzy logic for an interpretable music recommendation prototype. The model does not require historical user ratings, listening sessions, or manually labeled mood data. This makes it suitable for a content-based system and for educational settings where the main objective is to show how fuzzy inference works. The use of an ordinal Sugeno output also helps connect classification and ranking, because the same score can be interpreted as a mood label and compared with a target mood.

The main strength of the model is traceability. Each membership function and rule can be reviewed, and each recommendation follows from distance to a target mood score. Deep learning approaches may produce stronger predictive performance, but their decision path is less visible to users and project evaluators (Moysis et al., 2023). For an applied computing manuscript, the visible rule path is a practical advantage.

The model has clear limitations. The rules were manually designed and were not optimized against human mood annotations. Manual rules can encode intuitive assumptions, but they may not match how diverse listeners perceive music. The current implementation uses only four dataset features; acousticness, danceability, loudness, speechiness, and genre may improve prediction if added carefully. Mood perception remains subjective, so a song predicted as happy from audio features may still be perceived differently because of lyrics, memory, culture, or performance style.

The paper therefore distinguishes song mood from listener mood. The system predicts a song mood tendency from audio features; it does not infer the user emotional state. This distinction keeps the claim technical and avoids implying psychological emotion detection.

Compared with recent emotion-aware and intelligent recommendation research, the present system is modest in algorithmic scope but strong in practical explainability (Amiri et al., 2024; Jing et al., 2025; Tran et al., 2024). It provides a reproducible baseline that can be extended with validation data, hybrid features, or machine learning components. Future improvements could compare Sugeno outputs with human labels, measure recommendation satisfaction, or combine fuzzy rules with learned weights.

CONCLUSIONS AND RECOMMENDATIONS

This study developed a web-based song recommender using Sugeno fuzzy logic and Spotify audio features. Valence, energy, tempo, and mode are mapped into five mood levels: very sad, sad, neutral, happy, and very happy. The FastAPI backend calculates Sugeno output and returns recommendation or search results, while the React frontend provides mood selection and song-search interaction.

The results indicate that Sugeno fuzzy logic can support content-based recommendation when interpretability is more important than model complexity. The prototype is suitable as an applied baseline because its rules, scores, and ranking logic are visible. Before practical deployment, the rule parameters should be tested against listener judgments, expanded feature sets, and manually labeled mood datasets.

ADVANCED RESEARCH

Further research should validate the predicted mood labels with human participants and compare Sugeno output against machine learning baselines. A future model could include additional Spotify audio features, genre information, or lyrics-based sentiment. User satisfaction testing is also needed to determine whether the recommendations match listeners' perceived mood needs. Finally, the system can be extended into a hybrid recommender by combining fuzzy content scores with user preference history.

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