# Portugal's World Cup Shock: Reactions to the Loss Against Morocco

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**Abstract.** This project explores the public reaction on Twitter to Portugal's unexpected loss against Morocco during the 2022 FIFA World Cup. Using a dataset of 190,907 tweets described by 30 features, collected around the day of the match and the day before and after, we applied a combination of keyword filtering and Large Language Models (LLMs) to identify football-related content and classify sentiment toward the Portuguese national team. We conducted exploratory data analysis to identify peak activity periods, influential users, and trending topics. As focus, we analyzed sentiment patterns throughout the day, uncovering a significant spike in negative tweets during and immediately after the match. Topic-specific analyses uncovered criticism targeting coach Fernando Santos and star Cristiano Ronaldo, alongside widespread praise for Morocco's historic run. Visualizations such as line plots, bar charts, and heatmaps were used to support our findings. This study offers insight into how real-time sports events influence public sentiment and engagement on social media, especially when national expectations are disrupted by surprise outcomes.

**Keywords.** 2022 FIFA World Cup; Tweets; Large Language Models (LLMs)

## Introduction

On December 10, 2022, Portugal was eliminated from the FIFA World Cup following a surprising defeat by Morocco. This historic win marked the first time an African nation reached the World Cup semifinals, but also signaled what could be Cristiano Ronaldo's final appearance in a World Cup. This upset not only captured global attention but also ignited passionate reactions across social media, particularly on Twitter, where people shared their thoughts, opinions and feelings in real time. Platforms like Twitter have become powerful arenas for public discourse, especially during major global events like the World Cup, providing a massive volume of public sentiment data for analysis.
However, understanding how people's feelings evolve throughout the day, how they react, whether emotionally or informatively, and whether they show support or criticism toward key figures, is not straightforward and requires deeper exploration. So, in this project, we decide to explore the reactions to Portugal's loss against Morocco on Twitter, using Python and applying data science techniques.
Through careful data cleaning and preprocessing, manual keywords filtering, natural language processing (NLP), time-based analysis, and visualization techniques, we aimed to uncover key moments and sentimental spikes that shaped the online discourse surrounding this unforgettable match, demonstrating the power of data science to transform vast streams of semi-structured social media data into actionable insights.

## Data and Methods

In order to analyze public reaction on Twitter, we compiled data from three JSON files covering December 9–11, 2022 (the day before, the day of, and the day after the Portugal vs. Morocco match), collected via Twitter Standard Search API, with over 60k tweets per file. After concatenation, our dataset comprised 190,907 tweets described by 30 features, including:

- **Date and User ID:** created_at (timestamp), id
- **User Details and Info:** user, contributors
- **Location:** geo, coordinates, place
- **Entities:** entities, extended_entities, source
- **Reply/Quote Relations:** in_reply_to_*, is_quote_status, quote_*
- **Engagement Metrics:** retweet_count, favorite_count, favorited, retweeted
- **Content and Structure:** full_text, truncated, display_text_range

Of those features, 13 are Numerical, 14 are Strings, 4 are Boolean and 1 is a Datetime.

Our preliminary analysis highlighted that most tweets were in Portuguese, which made sense given our focus on Portugal, but we also identified *Undefined Language* Tweets ("Und"), ones where the language couldn't be detected reliably (super-short, all emojis, hashtags, links, informal/mixed languages, or bot spam), just adding noise and reducing the clarity of our graphs and findings. Since the sentiment analysis needs a real language to work, we dropped those mystery entries. Even without them, we still have over 7,800 tweets in 4 languages (Portuguese, English, Spanish, and French), more than enough to keep our graphs and models sharp. We also checked that most tweets received minimal engagement, (around 75%), while a handful achieved high visibility, with our most visible tweet peaking at 407 retweets and 1,663 likes. Ultimatly, we found that some columns were mostly empty and therefore removed. In contrast, other critical columns were fully populated and ready for analysis.

To prepare the dataset for analysis, we began by retaining only tweets in the four most prevalent languages to ensure our modeling tools would work reliably. Next, we narrowed the dataset to only the columns we really needed: the tweet timestamp for our time-series plots; the raw text for sentiment scoring, keyword matching, and modeling; the retweet and like counts to measure virality; and the language to confirm our filtering. Since none of these columns had missing values, we skipped any further cleaning. We then dropped duplicate tweets (based on identical text) and set the timestamp as our index to simplify our analysis. After checking the content of the user column, we also identified that some fields can be particularly relevant for our analysis: follower counts and screen names. To enrich our features, we pulled out hashtags and emojis and broke the timestamps into day, hour, and minute fields. Finally, we created a normalize version by lowercasing everything and removing URLs, mentions and multiple white spaces.

A key part of our work involved refining the dataset to football-related tweets, specifically those about the Portugal vs. Morocco World Cup match. To do this, we first applied a multilingual list of keywords like the teams and player names, match hashtags, and general football terms, to capture tweets explicitly referencing the game. Next, we used a Large Language Model (LLM), specifically Gemma 3, running locally through the ollama Python package, to evaluate the full text of each tweet and return True or False accordingly whether each tweet was about football. By combining the precision of keyword filtering with the flexibility of an LLM, we ensured our dataset included all relevant conversations while minimizing noise, setting the stage for accurate sentiment and topic analyses. These two approaches gave us a focused and low-noise dataset of 3619 match-specific tweets across 16 key columns.

To analyze and visualize the data, we made extensive use of some special Python libraries including:

- **pandas** and **NumPy** for data manipulation,
- **matplotlib**, **seaborn** and **plotly.express** for plotting,
- **collections.Counter, glob** and **re** for keyword frequency analysis and and file management
- **emoji** to to extract sentiment-rich emojis

Together, these methods enabled a structured approach to exploring public sentiment, engagement trends, and the emotional trajectory surrounding one of the World Cup's most shocking upsets.

## Results and Discussion

Finally, we analyzed our normalized tweet dataset to uncover the most notable findings aligned with our goal of capturing public reaction to Portugal's shock loss against Morocco in the 2022 World Cup. In our initial exploratory review of the 3,619 match-related tweets, we found that these came from just 1,895 unique users and generated roughly 2,500 retweets and 420 likes.

Our most detailed focused on four principal areas:

### Tweet Volume Evolution

Focusing on the match period and its key moments, we plotted tweet frequency at both hourly and minute granularity. As we can see in Figure 2, activity was low until just before 15:45 UTC, when Morocco scored, leading to a tweet volume spike of over 50 tweets per minute, capturing the immediate goal reaction wave. After the game restarted at 15:55 UTC, the number of tweets per minute remained around 20–25, and then exceeded 60 tweets per minute towards the end of the game (~17:00 UTC), when Portugal's elimination was confirmed.

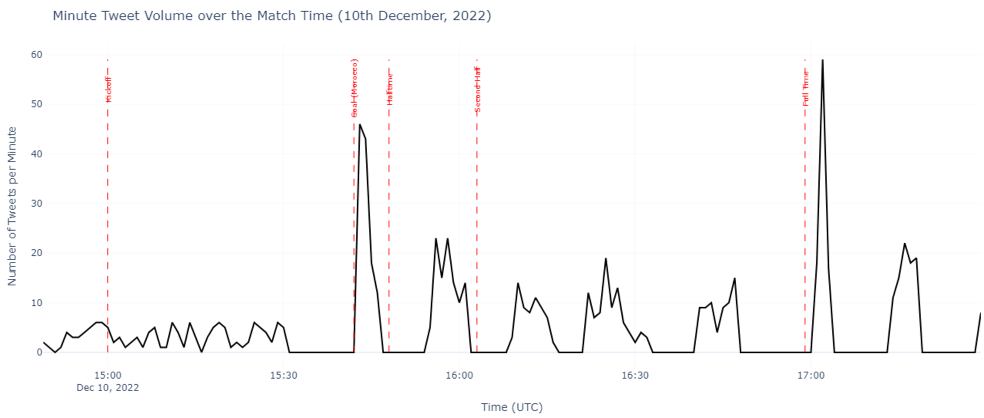


**Figure 2:** Minute Tweet Volume During the match POR vs MAR (10 December 2022).

### Sentiment Analysis

We used our LLM to label every cleaned tweet about Portugal's national team as Positive, Negative, or Neutral. Figures 2 and 3 reveal a clear arc of disappointment on December 10–11: before kickoff, tweets were few and mixed; once kickoff happened, negative tweets blew up, peaking right after the final whistle. That night, the criticism stayed strong before dying down overnight, but even the next morning (December 11), negative vibes still outnumbered hopeful or neutral ones. A smaller chat burst around midday was still mostly complaints, and by day's end the negative crowd had totally taken over, positive and neutral voices never bounced back after that loss.

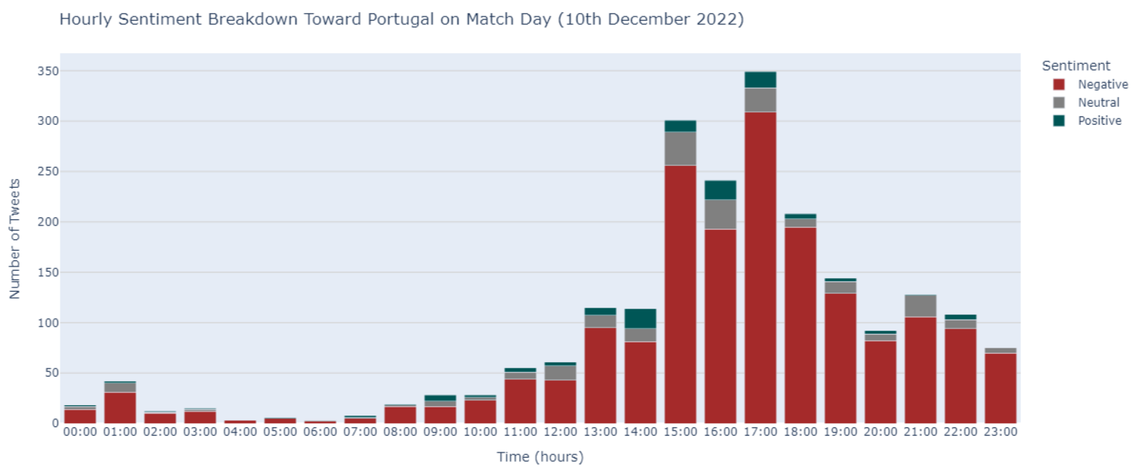


**Figure 2:** Hourly Sentiment Breakdown toward Portugal on Match Day (10th December 2022).

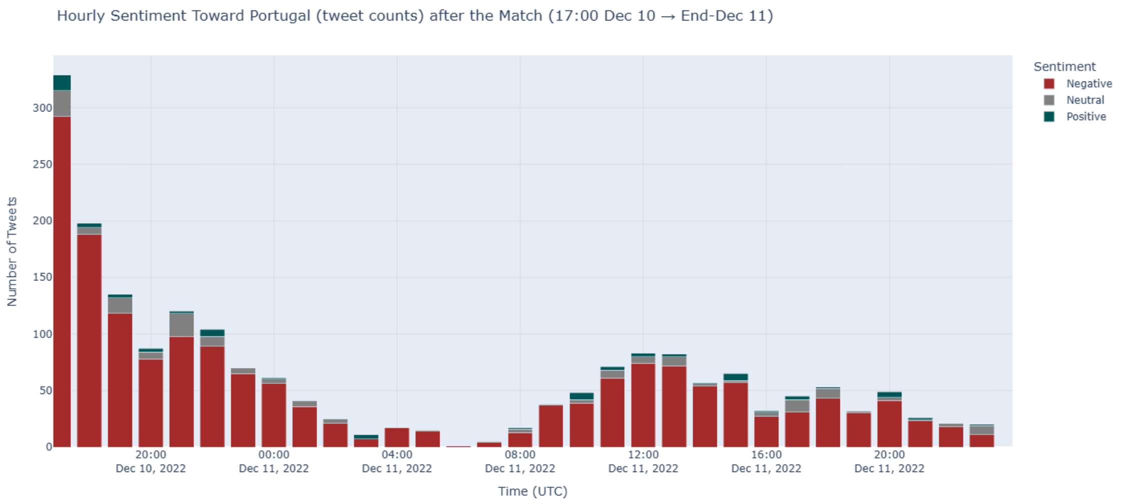


**Figure 3:** Hourly Sentiment toward Portugal after the Match Day (17:00 Dec 10 to the end of Dec 11).

## Keyword Analysis

Along with our sentiment analysis, the word frequency graph makes it clear that the negative tweets were focused as much on the team as on its most prominent figures. As Figure 4 shows, “Portugal”, “Santos”, “Fernando” and Ronaldo” top the list of negative keywords, signaling widespread fan discontent aimed at coach Fernando Santos and even the team’s star player. Terms like “bola,” “jogo,” and “mundial” further illustrate that frustration centered on the match itself and the loss to Morocco, helping explain why, despite a brief positive blip around 03:00 UTC on December 11, negativity swiftly regained dominance throughout the 28-hour window.

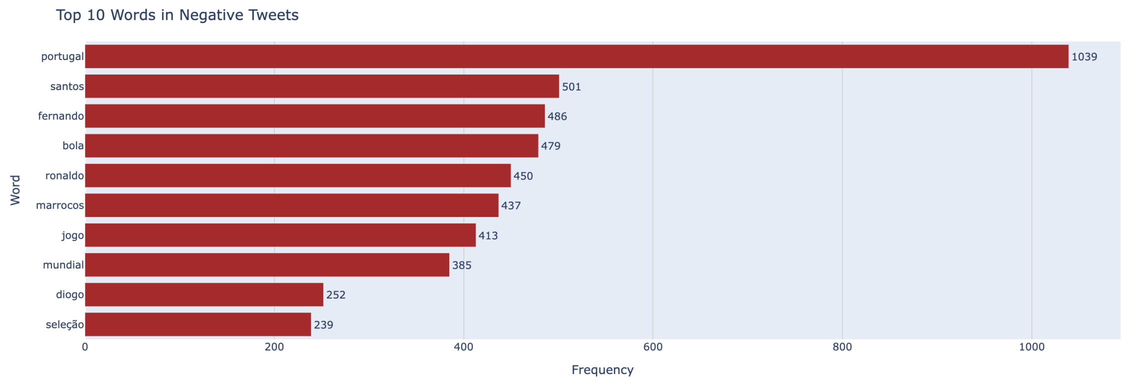


**Figure 4:** Top 10 words in Negative Tweets.

## Topic-specific Deep Dives

Because “Cristiano Ronaldo**”** and “Marrocos” emerged among the top keywords in negative tweets, we set out to answer two questions: *“Were people more supportive or critical of Cristiano Ronaldo after the match?”* and *“How did people talk about Morocco in the aftermath?*. To achieve this, we applied one LLM model to classify the tone of every tweet that mentions Cristiano Ronaldo as Sad, Critical, Supportive or Neutral. As a Figure 5 shows, the criticism dominated 60.7 % of all that tweets, while 20.7 % expressed Sadness, 13.7 % were Supportive, and just 4.9 % were Neutral.

Next, we used a second LLM to generate a global summary of all tweets related to Morocco, and that summary highlighted five major themes: Portugal’s shocking World Cup quarter-final defeat to Morocco; widespread admiration for Morocco’s historic run; questions about Fernando Santos’s tactics; a historical echo of Greece’s Euro 2004 upset; and growing excitement (and semi-final predictions against France) as fans looked ahead to Morocco’s next match.

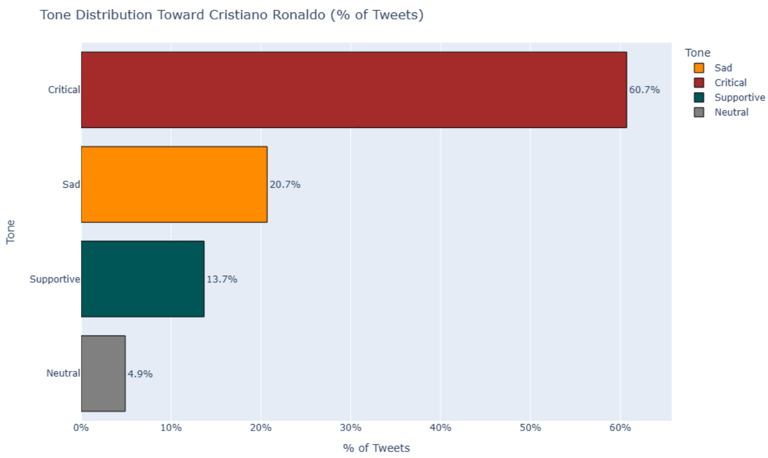


**Figure 5:** Tone distribution toward Cristiano Ronaldo (% of tweets).

## Conclusions

In conclusion, our analysis of Twitter activity surrounding Portugal's World Cup quarter-final defeat reveals a predominantly critical online discourse. Negative sentiment constituted 75 %–95 % of tweets throughout the 28-hour period, punctuated only by a brief surge of positivity in the early hours after the match. Word-frequency analysis shows that criticism was directed not just at the team as a whole, but squarely at coach Fernando Santos and even Cristiano Ronaldo, whose tweets were labeled Critical in 62.5 % of cases. Conversely, discussion of Morocco was overwhelmingly admiring, celebrating their historic run, questioning Portugal's tactics, and drawing comparisons to past tournament upsets. Together, these findings illustrate how social-media conversations can crystallize both collective disappointment in a favored side and genuine enthusiasm for the underdog, offering a nuanced window into fan sentiment in the heat of global competition.

One of the biggest challenges we faced was simply getting an LLM to perform reliably on sports talk: we used Gemma 3 to classify tweets about Portugal, but it often misread sarcasm or subtle emotions and even mixed up whether a tweet was about Portugal or another team. Getting solid accuracy was tough, and we know that beefier models like GPT-4 Turbo or Gemini Pro would handle those nuances way better, but their price tags were out of reach for this project. However, this could be something to explore in the future. Testing on a smaller subset of tweets to see how much they boost accuracy, and then experiment with light fine-tuning or model ensembles to find the sweet spot between performance and cost.

Moving forward, it would also be interesting to compare the sentiment about Portugal in their other matches to see how fan reactions differ after wins or losses, and whether the timing and magnitude of those positive or negative swings change across games.

## Statement of contribution & Acknowledgments

Patrícia Oliveira and Sérgio Patinha collaborated on data extraction, cleaning, and initial EDA, then jointly designed and implemented the LLM-based tweet classification, extracting polarity scores and leading the content feature extraction. Patrícia additionally developed the visualizations and drafted this final report. Miguel Almeida's research expertise informed both the visualization development and the overall analytical approach. Daniel Almeida contributed with ideas throughout our project meetings, though he did not directly work on the code or the report.

Finally, we would like to thank Professors Flávio Pinheiro and Vítor Manita for all the knowledge shared and for their invaluable guidance throughout the semester.

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