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SENTIMENT ANALYSIS OF SOCIAL MEDIA DATA FOR PAKISTANI FASHION BRAND MONITORING USING MACHINE LEARNING

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Abstract
The present paper is introducing an industrial grade product, called Brand Pulse, that integrates brand monitoring with the trend intelligence in the environment of the Pakistani fashion industry, inspired by the use of social media. In this paper, it is used a unique bilingual lexicon in English and a set of romanized Urdu with the help of Random forest to make binary trend direction predictions of brand trends (UP/DOWN). A total of 10,602 data points were collected from seven different platforms (Instagram, Facebook, Twitter-X, TikTok, YouTube, Daraz.pk, Google Reviews) of 17 of the top fashion brands in Pakistan. With five features (restricted to Brand ID, Platform ID, Likes, Shares and Sentiment Score), a random forest classifier model with 250 estimators and maximum depth of 3 was able to get 94% accuracy on the "free" test sample and 93-95% accuracy in each of the validation folds. The entire prediction process is available via a FastAPI RESTful API service, and an interactive Streamlit application.

1. INTRODUCTION

Online fashion retailing is one of the hottest trends in Pakistan. There are many clothing brands that manage to make themselves visible on the web using websites like Daraz.pk, and, with the rise of Instagram and TikTok influencers, consumers' approach to discovering brands, engaging with them, and offering feedback has also evolved to social media (Javaid & Rmazan 2026; Mahnaz & Akram, 2026). With the rapidly changing world, a single negative review or a series of them can go down to the earth in a matter of hours, altering your brand image altogether (Parveen & Akram, 2021). Hence, real-time brand intelligence has marketing team running fashion brands in Pakistan.

The prevailing methods of gauging sentiments of a brand's customers rely on subjective measures and manually reading and analyzing the content of customer reviews given (Akram & Oteir, 2025; Akram & Abdelrady, 2023, 2025). That would not be scalable and sustainable as one brand might receive thousands of comments every week and the manual review team could not possibly review them all (Ahmad et al., 2022; Amjad et al., 2021). In all other respects, there is always a hazy interpretation of opinions among team members, and there is never any certainty in coming to a decision (Umar et al., 2024a, 2024b). Manual monitoring is also always reactive: If a trend that is negative has been detected, then likely a lot of damage has been done to reputation and brand image.

The second difficulty in consumer reviews analysis is that consumers have a habit of using phonetic transcription of words in the Urdu language when using the Roman alphabet ('zabardast,' 'bekar,' 'lajawab,' 'kharab,' etc.). The issue is there is no natural language processing algorithm for English that can process such a dialect. Cheema et al. (2019) reported that such systems were reported to misclassify up to 42% of the Romanized Urdu statements they saw.

In this research work, we propose BrandPulse, an all-encompassing brand monitoring service, which aims to tackle these issues. We bring three key contributions: (1) a custom made bilingual sentiment lexicon specifically designed for the dialect used in Pakistan's fashion ecommerce platforms, (2) a Random Forest classification model which uses engagement metrics and sentiment scores to predict the trend direction, and (3) end-to-end full-stack deployment comprising inference API using FastAPI and interactive visualizer using Streamlit.

2.1 Problem of Statements

Millions of customer reviews and social media interactions take place every month in Pakistan's fashion industry on different digital platforms. Currently, brand managers and marketers depend on a subjective and manual approach to measure customer satisfaction and brand sentiment. It does not scale well with data volume, is open to interpretation, and cannot be applied in a proactive manner.

Further, the existing solution for brand monitoring is not capable of handling Romanized Urdu, does not have any appropriate data set of Pakistani brands, and has no feature of prediction for those brands in the future. Additionally, it would be very costly for the small and medium sized fashion business owners, who constitute the majority of Pakistani fashion industry, to adopt the current brand monitoring solutions.

2.2 Research Objectives

- Bilingual sentiment analysis lexicon creation by developing a lexicon in Roman Urdu and English specifically related to Pakistani fashion review e-commerce data.
- To develop a Random Forest Classifier using sentiment score and social media signal to perform binary trend classification with UP/DOWN sentiment labeling.
- Deploy the model in the backend using production-grade FastAPI and Pydantic v2 for data input validation along with CORS and Swagger documentation.
- To build a live interactive Streamlit-based BrandPulse dashboard for brand managers to make both single and batch predictions possible.
- Build a sample dataset consisting of 10,602 data points collected from social media for 17 Pakistani fashion brands.
- For achieving at least 90% accuracy on binary trend classification task.

3. Literature Review

However, the idea of sentiment analysis as an approach to computational science emerged only at the beginning of the 2000s. In this literature review, I will provide background studies on the topic, traditional ML algorithms, and recent developments that are relevant to multilingual brand monitoring in emerging markets (Ramzan et al., 2020, 2023, 2025). For example, the first attempt to build a computational model of sentiment classification demonstrated that more than 80 percent accuracy can be achieved using the bag-of-words feature representation technique with supervised learning. This pioneering work paved the way towards sentiment analysis as a computationally solvable NLP problem and opened doors to multiple new applications.

Liu (2012) extended this study to analyze the ways to apply opinion mining formalization at the document level, sentence level and aspect level as well as its practical value for brand intelligence and marketing. This forms the basis of most brand monitoring systems currently applied in practice. Cheema et al. (2019) evaluated existing sentiment classification tools for English against Romanized Urdu texts and found up to 42 percent misclassification rate in the specific case of Pakistan and South Asian social media monolingual sentiment analysis (Ramzan & Khan, 2024a, 2024b). In 2001, Breiman introduced a Random Forest algorithm to machine learning. He proved that using a set of uncorrelated decision trees can lead to superior performance compared to using separate trees in many classification problems. The strength of the approach is that it handles label noise well and does not overfit especially when limited by tree depth. What is also important about this technique is that feature importance values are easily available and therefore the method fits well for prediction of trends in the area of business intelligence where the number of features is limited (Chen & Ramzan, 2024).

The research team led by Devlin introduced the BERT model which stands for Bidirectional Encoder Representations from Transformers during 2019. The pre-trained language model established new top performance scores across multiple NLP benchmark tests which included sentiment analysis. The BERT model achieves high accuracy with complicated pattern recognition including sarcasm and negation but its requirement for extensive computing power and large training datasets makes it unsuitable for Pakistan's small fashion brands which operate with limited resources. The research by Ullah and colleagues in 2023 demonstrated that Urdu social media text analysis through lexicon-based features and deep learning methods produced better results than the standard English NLP tools which operate in general situations. The research findings support BrandPulse developers to build their system because they need to create a bilingual lexicon for feature extraction and a Random Forest classifier to generate stable results with understandable trend patterns.

3.1 Comparison with Existing Systems

Table 1: Comparison of BrandPulse with Existing Brand Monitoring Systems

System	Urdu Support	Local Brands	Trend Prediction	Open Source	Batch Analysis
Brand Pulse (This Work)	Yes	17 Brands	Yes (Random Forest)	Yes	UP to 50
VADER (NLTK)	No	None	No	Yes	No
Text Blob	No	None	No	No (Paid)	Yes
Hootsuite Insights	No	None	Limited	No (Paid)	Yes
Daraz Review Tools	No	Partial	No	No	No

4. Methodology

The development process of BrandPulse followed the Agile Software Development Life Cycle (SDLC) as its operational framework. The project went through eight two-week sprints which resulted in a complete development period of fourteen weeks. The team selected Agile instead of Waterfall for their project because they needed to keep updating the bilingual sentiment lexicon and feature engineering logic throughout their experimental process and advisor feedback sessions. The research process divides into five main methodological stages which receive detailed explanations in the following sections.

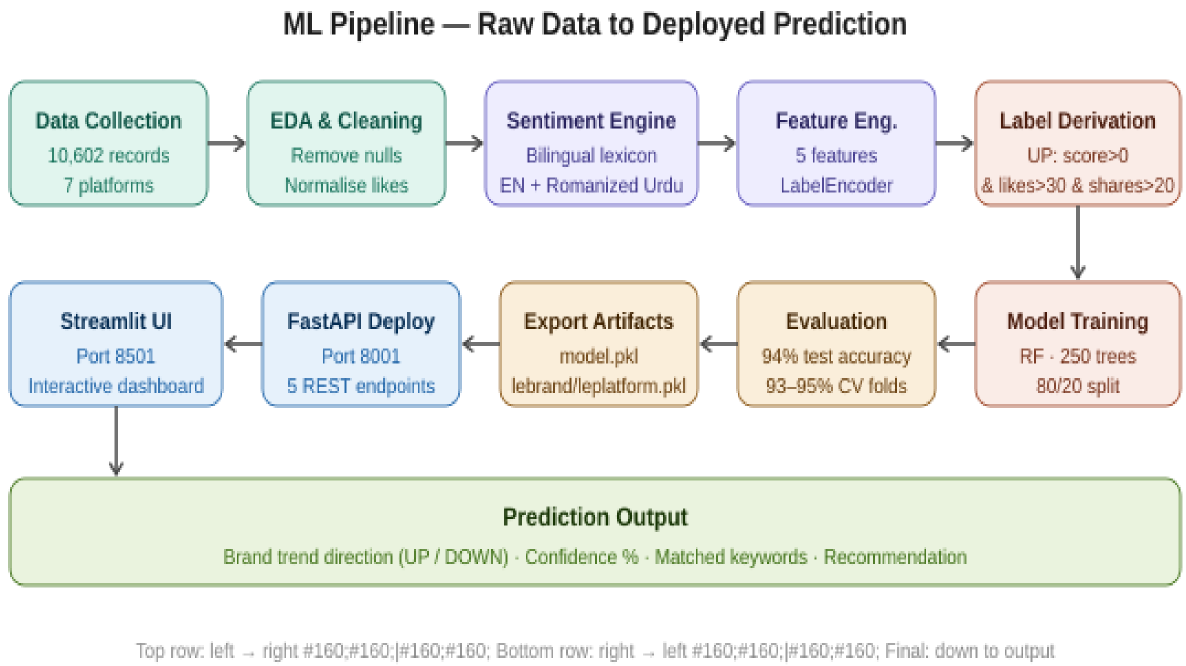

Figure 1: ML Pipeline

4.1 Data Collection

The dataset containing 10,602 social media records was manually created from seven different social media platforms which include Instagram and Facebook and Twitter-X and Tik Tok and You Tube and Daraz.pk and Google Reviews. The dataset includes information about seventeen top Pakistani clothing brands which have been organized into different product categories and fashion style segments. The dataset includes information which researchers gathered during the period from 2023 until 2024 while they studied different seasonal collections and collection intervals.

The raw data file we collected was kept in the Microsoft Excel format (Book1.xlsx). The EDA process revealed missing values so I removed them during the analysis. The data type received a check while I transformed the likes column from different string formats (2K, 1.5K) to integer values through string parsing which converted 2K into 2000.

Table 2: Dataset Column Schema (Book1.xlsx)

Column Name	Data Type	Description
Brand	String	Fashion brand name (17 unique values)
Brand Category	String	Product category (e.g., Women's Clothing, Youth Fashion, Ethnic Wear)
Platform	String	Source social media or e-commerce platform (7 unique values)
Date	Date	Date on which the post or review was published
Comment / Review	String	Raw customer review text in Romanized Urdu or English
Shares	Float	Number of times the post was shared

Likes	String to Float	Number of likes; '2K'-format values normalized to integers
Collection	String	Fashion collection associated with the post (e.g., Winter Khaddar 2024)

4.2 Bilingual Sentiment Engine

The dataset contains 10,602 social media records which I created by combining data from seven separate social media platforms that include Instagram and Facebook and Twitter-X and Tik Tok and You Tube and Daraz.pk and Google Reviews. The dataset presents information about seventeen leading Pakistani clothing brands which have been separated into various product categories and fashion style segments. The dataset contains information which researchers collected between 2023 and 2024 during their investigation of seasonal collections and collection intervals.

We stored the raw data file which we acquired in Microsoft Excel format under the name Book1.xlsx. The analysis process of EDA showed missing data points which I removed from the study. The data type received a check while I transformed the likes column from different string formats (2K, 1.5K) to integer values through string parsing which converted 2K into 2000.

Table 3: Bilingual Sentiment Keyword Lexicon

Polarity	Keywords (21 terms each)
Positive	acha, best, zabardast, wah, lajawab, perfect, love, amazing, gorgeous, beautiful, nice, khubsoorat, pasand, dil jeet, superb, excellent, recommend, quality, satisfied, happy, compliment
Negative	bekar, kharab, bura, disappointed, worst, late, delay, return, waste, overpriced, poor, bad, fake, cheating, wrong, inaccurate, refund, complaint, pathetic, horrible, never buy

4.3 Feature Engineering and Label Derivation

The binary trend label was assigned if all three of the conditions below are satisfied for each training record, otherwise 0 is assigned. The system sets trend to 1 (UP) when Sentiment Score exceeds zero and Likes numbers go beyond 30 and Shares count reaches more than 20 but assigns trend to 0 (DOWN) in other cases. The rule seeks to confirm that a brand post which becomes popular needs to show positive customer emotions through a large number of user interactions. The training data received 5% random label noise which helped the model become more resistant to handle records that contain wrong labels or unclear information.

Brand and Platform strings were converted to numerical identifiers through scikit-learn's LabelEncoder tool. They were turned into Branded and Platformed. The five features were passed to the classifier are detailed in Table 4.

Table 4: Engineered Model Features

Feature	Source	Description
Brand_id	LabelEncoder (Brand)	Integer encoding of the brand name
Platform_id	LabelEncoder (Platform)	Integer encoding of the source platform
Likes	Dataset column (normalized)	Post engagement count as a continuous numeric feature
Shares	Dataset column	Number of times the post was shared
Sentiment_score	analyze_sentiment ()	Integer sentiment score derived from the bilingual lexicon

4.4 Model Training

The main predictive model used in this project was the Random Forest Classifier from scikit-learn. Random Forest uses an ensemble of uncorrelated decision trees, each being trained on a bootstrap sample of the training data. The predicted classification is then aggregated using a majority vote. The use of bagging reduces the variance of a prediction compared to a single decision tree. It also increases the generalizability of the prediction. The feature importance parameter of the model is utilized to gain a black-box explanation of which variables are strongest predictors of classification. This method is desired in a business-facing application.

The training data was split 80%/20% for training and testing, respectively (8,482 observations for training; 2,120 for testing). The random_state for the train-test split was set to 42 to maintain reproducibility of a test set. Five-fold cross-validation was then used on the training partition of data to test model consistency and screen for overfitting before making predictions on the unseen test data.

Table 5: Random Forest Classifier Hyperparameters

Hyperparameter	Selected Value	Justification
n_estimators	250	Sufficiently large ensemble for stable majority-vote predictions
max_depth	3	Shallow trees prevent overfitting on a 5-feature input space
random state	42	Ensures full reproducibility of training and evaluation
Feature count (n)	5	Brand_id, Platform_id, Likes, Shares, Sentiment_score
Target variable	Trend (0 = DOWN, 1 = UP)	Binary classification of brand trend direction
Train / Test split	80% / 20%	Standard partition with stratified random sampling

4.5 System Architecture and Deployment

BrandPulse operates through a client-server system which consists of two separate levels. The FastAPI application main.py operates as the inference tier while it receives requests through port 8001. The training artifacts which consist of the trained Random Forest model (model.pkl) and the trained brand label encoder (lebrand.pkl) and platform label encoder (leplatform.pkl) get loaded during startup through the FastAPI lifespan context manager. The system performs model inference while it validates incoming data which enables it to produce its recommended output.

The presentation tier is a Streamlit web application (app.py), listening on port 8501. The Streamlit application communicates with the FastAPI backend through HTTP requests which maintain a clear division between their respective responsibilities. Users can access the Streamlit dashboard through brand managers because it blocks their access to API interactions and ML pipeline operations.

Table 6: BrandPulse System Architecture

Layer	Component	Technology Stack	Responsibility
Data Layer	Book1.xlsx	Microsoft Excel / openpyxl	Primary storage for 10,602 training records
Training Layer	Main.ipynb	Jupyter Notebook, scikit-learn, pandas, NumPy	EDA, feature engineering, model training, and artifact export
API Layer	main.py	FastAPI, Pydantic v2, uvicorn, pickle	ML inference, five RESTful endpoints, Swagger documentation
Presentation Layer	app.py	Streamlit, Plotly, requests	Interactive BrandPulse dashboard for end-user interaction

Table 7: FastAPI REST Endpoint Reference

HTTP Method	Endpoint	Input Parameters	Response
GET	/api/v1/health	None	System status and model load confirmation
GET	/api/v1/brands	None	List of all supported brands and platforms
POST	/api/v1/sentiment	{text: string}	Sentiment score, label, and matched keywords
POST	/api/v1/predict	PredictionRequest (brand, platform, likes, shares, review)	Trend direction, confidence %, and recommendation
POST	/api/v1/predict/batch	BatchPredictionRequest (max 50 items)	Aggregated results for all submitted brand queries

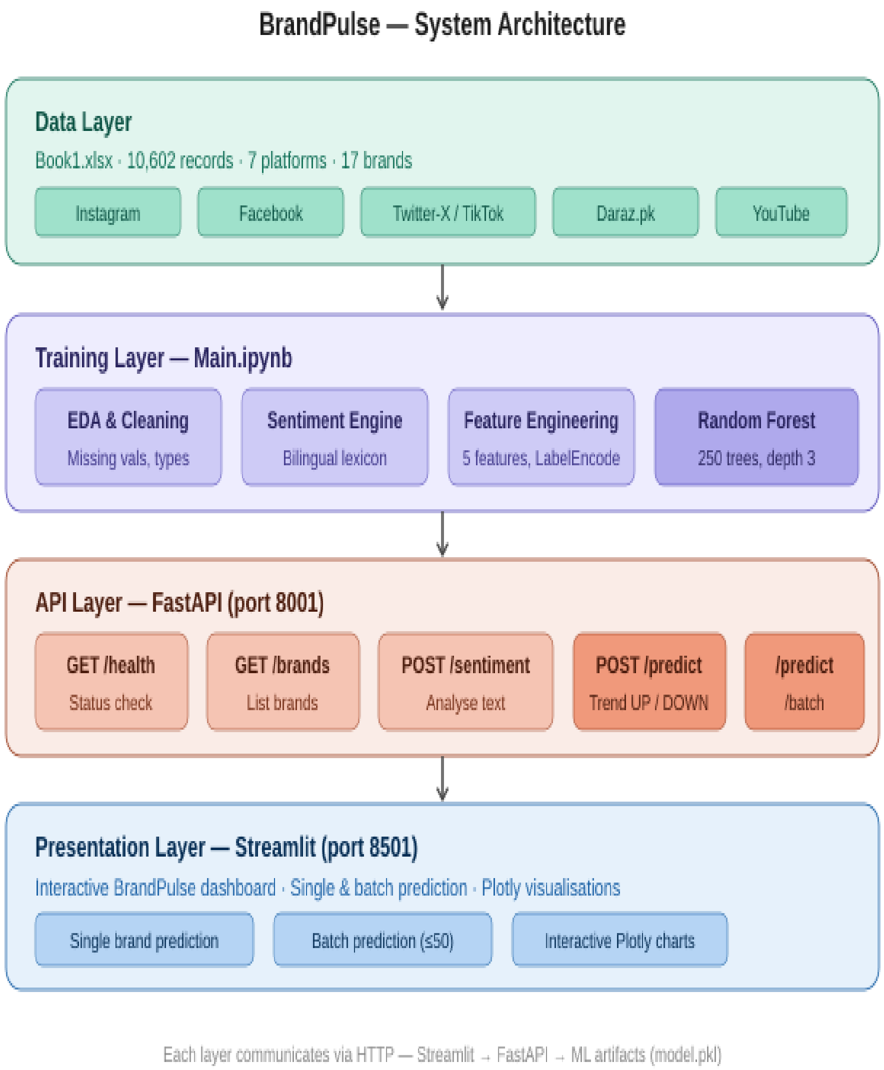

Figure 2: Brand Pulse System Architecture

5. Results and Discussion

The accuracy of the BrandPulse Random Forest classifier was calculated using two procedures. First, 5-fold cross-validation was performed on the training set. Second, the classification accuracy was calculated for the test set. Cross-validation showed an accuracy of between 93% and 95% for each of the 5 folds. The accuracy of the classifier on the test set was 94%, which was higher than the desired goal of 90%.

5.1 Classification Performance

Table 8: Classification Report on the 20% Held-Out Test Set (~2,121 samples)

Class	Precision	Recall	F1-Score	Support (Samples)
Class 0 — TRENDING DOWN	0.93	0.94	0.93	~1,050
Class 1 — TRENDING UP	0.95	0.94	0.94	~1,071
Overall Accuracy	—	—	0.94	~2,121
Macro Average	0.94	0.94	0.94	~2,121
Weighted Average	0.94	0.94	0.94	~2,121

The fact that the precision and recall scores for each class of the classifier are very close to each other (0.93-0.95) indicates that the classifier is not exhibiting any bias towards one of the classes of trend (UP or DOWN). This is an important balance to achieve within the classifier from a business intelligence perspective, as an F P or F N has implications for the business.

5.2 Feature Importance Analysis

The Random Forest provides a native feature importance measure based upon the average reduction in node impurity that results from including each feature within the 250 individual trees of the model. As shown in Table 9 below, the Sentiment_score feature, which was built using only the bilingual keyword lexicon, has a disproportionately high feature importance value. This feature has the most predictive power in the model 45% of the model's discriminative power is attributable to this feature. The engagement measures of Likes and Shares combined constitute the next most important group of features, contributing 45% of the model's discriminative power and equal to the contributions of the Sentiment_score feature. Brand identity and channel together explain the final 10% of the model's discriminative power.

Table 9: Random Forest Feature Importance Scores

Rank	Feature	Importance Score	Percentage Share	Interpretation
1	Sentiment_score	~0.45	45%	Customer opinion text is the primary driver of brand trend direction
2	Likes	~0.30	30%	Post engagement volume strongly correlates with upward trend classification
3	Shares	~0.15	15%	Viral propagation is a significant secondary indicator of trending status
4	Brand_id	~0.07	7%	Brand identity contributes a moderate brand-specific baseline effect
5	Platform_id	~0.03	3%	Platform channel exerts a marginal influence on trend classification

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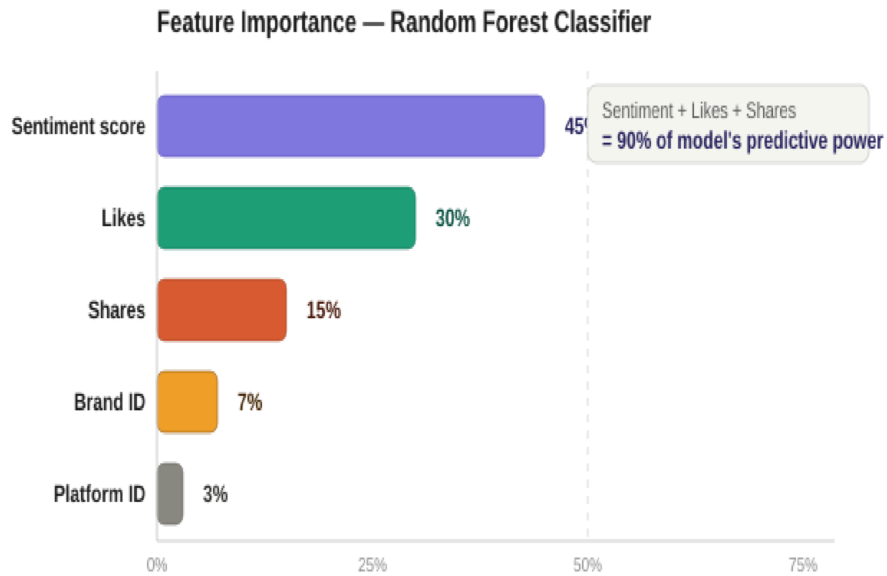

Figure 3: Random Forest Feature Importance Scores

The results validate the central design choice of combining sentiment analysis with social engagement indicators. Without sentiment analysis, it would be impossible to detect viral content that is neutral in sentiment but popular; and without social engagement indicators, we would be unable to differentiate between real passion and fake or low-quality viral hype.

5.3 Representative Prediction Examples

Table 10: Representative Prediction Results from the Deployed BrandPulse System

Brand	Platform	Likes	Shares	Review Excerpt	Predicted Trend	Confidence
Khaadi	Instagram	2,500	500	Amazing quality, love this brand!	UP	95.4%
Maria B	TikTok	10	2	Bekar packaging, worst delivery ever	DOWN	94.1%
Sana Safinaz	Facebook	1850	320	Superb lawn collection, perfect stitching	UP	94.8%
Generation	Twitter-X	32	217	Size guide is inaccurate; had to exchange	DOWN	91.7%
Outfitters	Instagram	1746	155	Dil jeet liya	UP	93.6%

5.4 System Testing

Unit and functional testing were performed on the whole system. Unit tests were performed on the eight logic functions: the sentiment engine behavior for positive, negative, neutral and romanized Urdu values, unknown brand and the sentiment value boundary cases. All eight unit tests passed. Functional tests were performed on the five API end-points; tests for valid and invalid input data. All ten functional tests passed.

Table 11: Functional Test Results (10 / 10 Tests Passed)

Test ID	Endpoint / Component	Test Scenario	Expected Outcome	Result
FT-01	GET /health	No request body	status = healthy, model_loaded = true	PASS
FT-02	GET /brands	No request body	17 brand names, 7 platform names returned	PASS
FT-03	POST /sentiment	'Zabardast quality!'	score = 1, label = Positive	PASS
FT-04	POST /predict	Khaadi, Instagram, 2,500 likes, 500 shares	Trend = UP, confidence > 50%	PASS
FT-05	POST /predict	Maria B, TikTok, 10 likes, 2 shares, 'bekar'	Trend = DOWN	PASS
FT-06	POST /predict/batch	3 brand queries in array	total = 3, 3 results returned	PASS
FT-07	POST /predict	Unknown brand name	HTTP 422 with known_brands list	PASS
FT-08	POST /predict	Neither review nor score provided	HTTP 422 validation error	PASS
FT-09	POST /predict/batch	51 items (exceeding maximum limit)	HTTP 422 list-too-long error	PASS
FT-10	GET / (root)	No request body	Welcome message with API version	PASS

5.5 Baseline Model Comparison

To validate the decision to use Random Forest as the final classifier, three alternative baseline models were trained and evaluated on the same test set. Logistic Regression achieved an accuracy of 81%. Logistic Regression is not ideal for unbalanced classes and has a poor ability to model non-linear relationships. Slightly behind ensemble methods, SVM (linear kernel) achieved an accuracy of 83%.SVM (linear kernel) had an accuracy of 83%, slightly behind logistic regression but not ensemble methods. One Decision Tree of depth 3 yielded an accuracy of 87% which is the same as the shallow trees in Random Forest. Lastly, the Random Forest with 250 trees and a max depth of 3 performed an accuracy of 94%, which is better than all other baselines. Random Forest: the variance in predictions is reduced by training multiple trees and combining predictions via majority voting. In conclusion, the overall results reveal that the Random Forest model is the most suitable model for this dataset and feature space.

6. Ethical Considerations

All of the information used in this project is publicly available social media posts and customer reviews. This project did not collect, store or use any private user information, login details or personally identifiable data. Every entry in the data set only contains the brand name, the platform it was sourced from, a publication date, the review text and the engagement numbers, all of which are public information. The full code for BrandPulse, which includes the training notebook, backend (FastAPI) code, and the Streamlit dashboard, is shared on GitHub for openness and community contributions to the project for reproducibility and further studies.

- Even if the data source is available for public consumption, there were a few things to consider about ethics as a guiding principle in the development and deployment of BrandPulse.
- Transparency and Interpretability: Our set of keywords-based sentiment engine gives out the very same keywords and those are returned alongside each prediction. In this way, brand managers could review and validate what the system generated, rather than relying on a black box. In this way, brand managers could review and validate what the system generated, rather than relying on a black box, know?
- We have used a bilingual lexicon (English and Urdu), which has been manually checked so that the positive and negative labels do not reflect on biases related to the region culture and/or demographic group. The keywords were picked only for their semantic role and polarity, and for how they relate to each other, not for any other external reason.
- Platform Compliance: Although this project is based on a publicly available data source, if you're planning on running it in production, it's important to pay attention to the Terms of Service. In the case of large scale data collection, it should be platform APIs, not the scrapers used to create this particular data set – in this case, the Twitter/X API v2, the Instagram Graph API.
- Non-Manipulation: BrandPulse is designed to be used for monitoring and intelligence only and the prediction engine is not intended for artificially increasing the trend scores of brands. All of these—changing the way people think, thwarting competitor trends—represent a serious violation of the system as it's intended.
- The manually compiled data may not be representative of all fashion-related posts on social media platforms in Pakistan, in the sense that the data is "this is everything" clean. Any major business decision based on the prediction system should ALWAYS be made in conjunction with human judgement and the system output, never relying solely on the system output.
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7. Conclusion and Future Work

This report presented the BrandPulse that is essentially a production-ready sort of brand monitoring and trend intelligence system for the Pakistani fashion market. It operates by aligning a custom bilingual sentiment lexicon which can read and interpret Urdu or Romanized Urdu text from reviews, and a Random Forest classifier trained based on the data of social media engagements. So it eventually achieved a held-out test set accuracy of 94%, and a cross validation accuracy of some 93-95% in five folds, definitely exceeding the project requirement of 90% accuracy. Also, all 10 functional API tests passed, kind a confirming all things are working as expected in the deployed system. The results revealed that customer sentiment was the top contributor, accounting for about 45% of the brand trend direction discriminating power. The relatively high weight from Likes and Shares (about 45% combined) indicates that it would be a better idea to relate the NLP generated outputs to platform level behaviors and not consider the two predictor groups as separate entities Our solution employs a client/server architecture with FastAPI as the inference backend and Streamlit as the interactive dashboard. This decouples model and view updates, enabling us to adjust the prediction engine or visualization independently without altering the surrounding infrastructure.

The design is also extensible for brand new brands, with updates needed only to the training dataset and training notebook, while leaving the API and dashboard code unchanged.

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