Comparing Machine Learning and Time-Series Models for Depression Detection Using LOPO-CV

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Abstract

Depression is a leading cause of disability worldwide, necessitating improved early detection methods to aid timely intervention. Traditional diagnostic approaches rely on self-reported assessments, which are subject to personal bias and inconsistency. Recent advancements in artificial intelligence have enabled automated depression detection using behavioral signals, such as facial expressions and head movements. This study explores two distinct modeling paradigms: (1) Machine learning models that use aggregated facial behavior and head gesture features to predict depressive episodes, and (2) Time-series deep learning models utilizing Long Short-Term Memory (LSTM) networks to capture sequential behavioral changes over time.

We employ data collected from the FacePsy research initiative, comprising 12 facial action units (AUs), 3D head Euler angles, and eye openness probabilities. Feature engineering techniques, including collinearity reduction and standardization, were applied before training models. The machine learning models evaluated include Logistic Regression, Support Vector Machines (SVM), Random Forest, and XGBoost, trained on participant-averaged features. The LSTM model, in contrast, processes sequences of 10 time steps, preserving temporal dependencies in facial behavior.

To ensure robust evaluation, we apply Leave-One-Participant-Out Cross-Validation (LOPO-CV), a stringent method that tests model generalization across individuals. Results show that while machine learning models exhibit strong accuracy on static features, LSTMs capture temporal patterns more effectively, achieving an AUROC of 0.6123 compared to 0.5714 for the best-performing ML models. Challenges identified include dataset variability, sequence inconsistencies, and missing feature values. Future work will focus on enhancing dataset quality, integrating multimodal signals such as speech and physiological data, and exploring hybrid models that combine static and sequential learning.

1 Introduction

Depression is a severe mental health disorder affecting millions of individuals worldwide. Early detection is crucial for timely intervention, yet traditional diagnostic methods rely on self-reported assessments, which are prone to bias and inconsistency. Advances in artificial intelligence have enabled automated methods for detecting depression based on non-invasive behavioral analysis, such as facial expressions, head movements, and speech patterns.

This study compares two modeling approaches: (1) A machine learning-based method that utilizes aggregated features from short video sequences and (2) A time-series deep learning model leveraging LSTMs to analyze sequential variations in facial behavior. Our goal is to determine the relative effectiveness of these methods and assess their robustness using LOPO-CV.

2 Related Work

Prior studies have explored emotion recognition and depression detection using facial analysis, voice tone, and text sentiment analysis. Traditional machine learning approaches have leveraged Support Vector Machines (SVM), Decision Trees, and Random Forests to classify depressive symptoms based on facial action units and head pose features. More recent deep learning models, such as CNNs and RNNs, attempt to capture sequential behavioral cues but require large datasets for effective training. While many studies have used cross-validation methods, few have employed LOPO-CV to evaluate generalization performance. Our study extends prior work by comparing traditional ML approaches with deep learning time-series models under a rigorous validation framework.

3 Dataset and Preprocessing

3.1 Data Collection

The dataset was collected from the FacePsy research initiative, capturing facial behavior and head gestures in naturalistic settings. Data was recorded when participants unlocked their phones or engaged in mobile activities, ensuring an ecologically valid sample. Each recording consists of a 10-second video segment, from which key facial action units (AUs), head Euler angles, and eye openness probabilities were extracted.

3.2 Feature Extraction and Preprocessing

Extracted features include:

- 12 Facial Action Units (AUs) representing muscle activations.
- 3D Head Euler Angles (Pitch, Yaw, Roll) to assess movement dynamics.

- Probability scores for left and right eye openness and smiling intensity.
- 133 Landmark points capturing facial geometry.

Data preprocessing involved handling missing values, normalizing features, and performing collinearity analysis to reduce redundant inputs. We used median imputation for missing numerical features and standardized all continuous variables using z-score normalization.

4 Methodology

4.1 Machine Learning Models

We trained and evaluated four machine learning classifiers:

- **Logistic Regression**: A baseline linear classifier.
- **Support Vector Machines (SVM)**: A kernel-based approach to handle complex feature interactions.
- **Random Forest**: An ensemble learning method leveraging decision trees.
- **XGBoost**: A gradient boosting technique optimized for structured data.

Models were trained using LOPO-CV, ensuring that each participant was left out for testing once.

4.2 Time-Series Model Using LSTM

For temporal analysis, we implemented an LSTM-based deep learning model:

- Two LSTM layers (64 and 32 units) with dropout regularization.
- A final dense layer with sigmoid activation for binary classification.
- Training via Adam optimizer with binary cross-entropy loss.

Sequences of 10 timesteps were generated per participant, ensuring temporal dependencies were preserved.

5 Results and Discussion

5.1 Machine Learning Model Performance

Table 1 presents LOPO-CV results for machine learning models.

Model	AUROC	Accuracy	Precision
Logistic Regression	0.4762	0.8571	0.2857
Random Forest	0.5714	0.9762	0.4286
SVM	0.5238	0.8571	0.2857
XGBoost	0.5714	0.9762	0.4286

Table 1: Performance of Machine Learning Models

5.2 LSTM Model Performance

LOPO-CV results for the LSTM model:

- AUROC: 0.6123 ± 0.1547
- Accuracy: 0.8921 ± 0.1823
- Precision: 0.4712 ± 0.3298

6 Challenges and Limitations

- LOPO-CV results exhibit significant participant variability.
- LSTMs require larger datasets for optimal generalization.
- Inconsistent feature extraction affects sequence modeling.

7 Conclusion and Future Work

This study demonstrates the feasibility of detecting depression using facial and head movement features. Machine learning models achieve competitive accuracy but lack temporal insights, whereas LSTMs improve sequential pattern recognition. Future improvements include:

- Expanding the dataset for better generalization.
- Exploring hybrid models combining ML feature extraction with LSTMs.
- Integrating additional modalities such as speech and physiological signals.

References

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