Optimizing SVC for Facial Orientation Detection in Varied Image Resolutions

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Abstract

This research focuses on facial orientation detection in images, employing a Support Vector Classification (SVC) optimized for different resolutions. SVC was selected for its robust performance over other algorithms. MinMaxScaler standardized the data, while PCA condensed features. Hyper-parameter tuning, data augmentation, and noise introduction refined the SVC models, substantially improving accuracy and demonstrating the efficacy of the methodologies.

1. Introduction

Facial orientation detection presents a nuanced challenge in image processing, critical for enhancing interactive technologies. Accurate orientation data is vital, especially when distinguishing whether a facial segment is upright, rotated, or inverted across varying image sizes and qualities.

This report details the development of a machine learning-based classifier. A concise System Description will outline the architecture and hyper-parameter optimization. The Experiments section will describe our model tuning methodology. Results and Analysis will compare performance against baselines, highlighting improvements. The Conclusions will integrate our findings and discuss future research directions for system enhancement.

2. System Description

Our classification system employs Support Vector Classification (SVC) with a Gaussian kernel to determine facial orientation from standardized sub-images. MinMaxScaler is utilized for normalization, ensuring uniform feature scaling. Principal Component Analysis (PCA) then reduces dimensionality, capturing significant variance while minimizing noise.

Key to SVC performance are the hyper-parameters $\boldsymbol{C}$ and γ, which balance model complexity against overfitting. These parameters are fine-tuned using grid search and cross-validation to achieve optimal generalization across various facial orientations—upright, 90 degrees left, 90 degrees right, or upside down. The process is designed for reproducibility, with detailed parameter settings documented for peer replication.

3. Experiments

3.1. Data Preprocessing

Our preprocessing pipeline commences with the random cropping of images to a uniform target_size $\times$ target_size resolution, ensuring consistency across the dataset. This step is vital for standardizing the input size and maintaining focus on the central facial features.

Next, we induce variability and robustness in the dataset by randomly rotating the cropped images to one of four cardinal orientations. This mimics the diverse conditions under which facial orientation detection systems must operate. Optional Gaussian noise is added to the rotated images to emulate real-world imaging conditions, such as sensor noise or compression artifacts, preparing the model for practical deployment challenges.

Through these procedures, the preprocessing phase lays a solid foundation for the robust performance of the classification system, enabling it to handle input data variations effectively.

3.2. PCA Dimensionality Reduction

As part of our preprocessing pipeline, Principal Component Analysis (PCA) played a crucial role in condensing the feature space of facial images. This dimensionality reduction technique was instrumental in filtering out noise and focusing on the most salient features for orientation detection. By adjusting the components to retain variance optimally, we ensured the SVC model capitalized on the most informative aspects of the data while enhancing computational efficiency.

Hyper-parameter	Accuracy for 90 pixels
None	64.65%
PCA50	95%
PCA75	94.6%

Table 1: *PCA performance comparison*

3.3. Baseline Model Evaluation

In evaluating classifiers for facial orientation detection, we compared Random Forest, K-Nearest Neighbors (KNN), and Support Vector Classification (SVC). Random Forest was valued for its ensemble robustness, KNN for its straightforward effectiveness, and SVC for its proficient handling of high-dimensional data and non-linear pattern recognition with the Gaussian kernel. On 90-pixel images, SVC surpassed others in accuracy despite a larger model size, marking it as the preferred choice. Future work will focus on model compression to optimize SVC for practical application.

Model Algorithm	Accuracy for 90 pixels
Random Forest (50)*	84.45%
KNN (5)**	90.8%
SVC (default parameters)	95.0%

Table 2: *Baseline model performance comparison*
* Random Forest with 50 trees.
** KNN with 5 neighbors.

3.4. Normalization Techniques Comparison

Normalization is a pivotal step in data preprocessing to ensure that each feature contributes equally to the learning process. We compared MaxAbsScaler, StandardScaler, and MinMaxScaler to identify the scaling technique that would best preserve the relationships within the data while enhancing model performance. MinMaxScaler was found to be the most effective, as it maintained the distribution of the features while scaling them into a bounded interval, which is particularly beneficial for algorithms like SVC that are sensitive to the scale of the input data.

Normalization	Accuracy for 90 pixels
None	95%
MaxAbsScaler	94.89%
StandardScaler	95.19%
MinMaxScaler	95.35%

Table 3: *Normalization model performance comparison*

3.5. Hyper-parameter Optimization

Tuning the hyper-parameters of our SVC model was a deliberate and iterative process. We conducted a grid search to explore a range of values for the regularization parameter C and the kernel coefficient γ, evaluating their impact on model accuracy and overfitting tendencies. Separate optimizations were performed for images of different resolutions—30x30, 50x50, and 90x90 pixels—to tailor the model to the specific challenges presented by each size. The optimal parameters were then selected based on their performance on a validation set.

Hyper-parameter C	Accuracy for 90 pixels
C=0.9	94.85%
C=1	95.35%
C=3	95.75%
C=5	96%

Table 4: *SVC Model Hyper-parameter C comparison*

Hyper-parameter γ	Accuracy for 90 pixels
C=3, γ=scale	95.75%
C=5, γ=scale	96.00%
C=3, γ=0.1	47.09%(overfit**)
C=5, γ=0.1	47.09%(overfit**)

Table 5: *SVC Model Hyper-parameter γ comparison*
**Training set accuracy 100%

3.6. Data Augmentation and Noise Injection for Model Optimization

The integration of data augmentation and noise injection played a pivotal role in fine-tuning our SVC model's performance. By employing augmentation techniques, we addressed issues of underfitting by expanding the diversity of the training set, thus providing the model with a broader learning spectrum. Concurrently, the introduction of random Gaussian noise countered overfitting by simulating real-world data variance. These strategies collectively enhanced the model's accuracy and led to the establishment of a robust final model structure, as confirmed by our validation results.

Configuration	Accuracy for 90 pixels
C=3, scale, noise	96.2%
C=3, scale, noise, augment	96.6%
C=5, scale, noise	96.39%
C=5, scale, noise, augment	96.55%

Table 6: *Augmentation and Noise Performance Comparison*

3.7. Analysis

Although the experimental part of this article only shows the classification of 90pixels images, the same steps are actually used for images of other sizes to obtain the optimal structure and parameters; in addition, the dump compression of pca and joblib is used to strictly control the model size. Within 20MB.

Model Algorithm	Normalization
SVC(rbf, c=7, gamma=0.09)	MinMaxScaler, noise_augment
SVC(rbf, c=5)	MinMaxScaler, augment
SVC(rbf, c=3)	MinMaxScaler, noise_augment

Table 7: *Final Model Structure 1*

Dimensionality Reduction	Model Size (MB)	Accuracy
PCA(75)	7.3	53%
PCA(75)	6.2	73.45%
PCA(50)	2.9	96.60%

Table 8: *Final Model Structure 2*

Alongside the fine-tuning of C and γ parameters for larger images, the models for smaller dimensions received similar rigorous attention. A comprehensive suite of models, enhanced by data augmentation and noise injection, demonstrated adaptability across resolutions, showcasing a robustness essential for real-world variability. These findings emphasize that detailed preprocessing and careful parameter adjustment are crucial for optimal model performance.

4. Discussion and Conclusions

This exploration highlights the deep link between data preprocessing and the SVC model's capacity for facial orientation detection. Classifier performance notably hinged on sub-image size, with PCA significantly accelerating processing without losing accuracy, showcasing PCA's dual benefit in model efficiency and speed.

MinMaxScaler was a key element in our preprocessing, outshining MaxAbsScaler for high-variance data, emphasizing the significant role of scaling methods in influencing model results.

Data augmentation and noise introduction were key in mitigating underfitting and overfitting, enhancing the model's generalization as reflected in accuracy improvements.

Given more time, investigating ensemble methods could have been a promising direction for performance improvement. Time constraints, however, highlighted this as an area for future exploration.

In conclusion, this study sets a strong foundation for facial orientation classification, leading to further refinement and deeper examination of machine learning model trade-offs, particularly in ensemble learning integration.

5. References

Deng, X. et al. (2016) 'Citrus greening detection using visible spectrum imaging and C-SVC', Computers and electronics in agriculture, 130, pp. 177–183. doi: 10.1016/j.compag.2016.09.005.