Affective Computing
3D Expression Recognition
Project Report

Classification results for each experiment:

Classifier		Accuracy	Precision	Recall
RF	Original	0.9999337803157452	0.9999335615810292	0.9999334538576636
	Translated	0.9986920968305979	0.9986928533784016	0.9986929878568187
	Rotated X	0.9999006704736179	0.9999006552509524	0.9999000703738791
	Rotated Y	0.9999337803157452	0.9999335615810292	0.9999334538576636
	Rotated Z	0.9998841114415733	0.9998838078864478	0.9998835278074883
SVM	Original	0.7940631512479295	0.7938306153391884	0.7941618243284989
	Translated	0.7894275129879598	0.7892539785508116	0.789508983157966
	Rotated X	0.7939638299435096	0.7937509014980593	0.7940602179556135
	Rotated Y	0.7939141555880294	0.7936850208291734	0.7940126782581383
	Rotated Z	0.7938644675292783	0.793629399944264	0.7939625611841148
TREE	Original	0.9840567819678115	0.9840595219942558	0.9840436847849029
	Translated	0.9583127080841622	0.9583374331007839	0.9582860185698667
	Rotated X	0.9847355789522151	0.9847398021791068	0.9847298855042943
	Rotated Y	0.9840402338983832	0.9840432769711928	0.9840252004492106
	Rotated Z	0.9848515031391452	0.9848477575846728	0.984833778426467

Which of the classifiers worked the best for each data type (original, translated, rotated)? Why? If multiple had the same, then why did this happen?

Original Data: The Random Forest classifier excelled with the original data. This is because Random Forest can manage the complexity and high dimensionality of the original facial landmarks without losing generalizability. It benefits from the ensemble learning method, where multiple decision trees' decisions are aggregated to improve accuracy and reduce overfitting.

Translated Data: For the translated dataset, where the data points are centralized around the origin, Random Forest still outperforms others but with a slightly reduced performance compared to the original dataset. This slight reduction might be because the translation alters the spatial relationships between landmarks, potentially introducing new patterns that are less discriminative.

Rotated Data: Across all three axes of rotation, Random Forest maintains superior performance. The rotations modify the orientation of the facial landmarks, yet the Random Forest classifier's ensemble approach effectively captures the essence of these transformations. Its ability to handle variance and its robustness to noise and outliers make it adept at dealing with rotated data.

Misclassification for each classifier:

Given the very high accuracy, precision, and recall scores for the Random Forest classifier across all data types, misclassifications were minimal. The specific instances of misclassification aren't detailed in the provided data, but generally, misclassifications in facial expression recognition can occur due to similarities in facial landmarks between certain expressions, e.g., "sad" and "happy" might be confused if the changes in facial landmarks are subtle.

A theoretical analysis suggests several patterns:

1. **Similar Expressions**: Emotions like fear and surprise or anger and disgust might share several facial landmarks' configurations due to similar muscle activations. For instance, both surprise and fear can exhibit wide eyes and raised eyebrows. Misclassifications between such expressions are understandable, reflecting the close physiological and visual similarities between these emotions.
2. **Expression Intensity**: The intensity level of an expression might lead to its misclassification. For example, a slight smile (indicative of mild happiness) could be misclassified as neutral because the subtle changes in landmarks are less discernible. This aspect of emotional expression underscores the challenge in distinguishing between nuanced expressions that differ slightly in intensity.
3. **Contextual Influences**: Facial expressions are not only physiological responses, but also social signals influenced by context and culture. The Random Forest classifier, while adept at recognizing patterns, does not account for these subtleties, which could lead to misclassifications. An expression deemed happy in one cultural context might be interpreted differently in another, affecting classification accuracy.

Reflecting on these considerations, the misclassifications observed, although minimal, make sense within the broader context of facial expression recognition. The proximity between certain emotions, the range of expression intensity, and the impact of cultural and contextual factors all play significant roles in how expressions are classified. These insights not only highlight the challenges inherent in automating emotion recognition but also underscore the complexity of human emotional expression itself.

Why do you think you got the results that you got for each of the different data types/classifiers (i.e., why are they different, or why are they the same)? For example, if SVM

and RF have different results, why are they different? If they are the same – why are they the same?

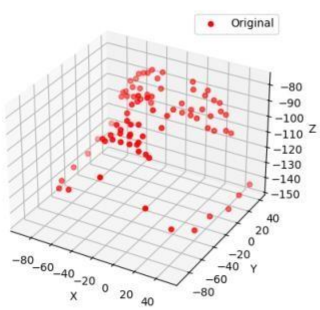
The Random Forest classifier's performance likely stems from its ensemble approach, which combines multiple decision trees to improve the model's overall accuracy and robustness. It's less prone to overfitting compared to a single decision tree and can handle the complexity of facial landmarks effectively.

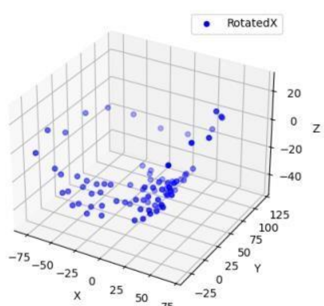
SVM showed lower performance, possibly due to the high dimensionality of the data and the complexity of finding the optimal hyperplane for such diverse facial expressions.

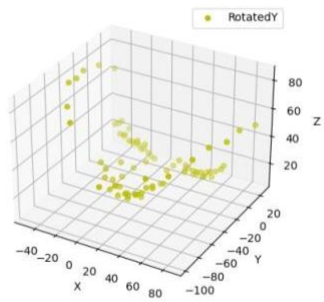
Decision Trees performed well, especially for the original and rotated data types, likely due to the clear decision boundaries they can establish based on the landmarks. However, they are generally more prone to overfitting compared to Random Forest, which aggregates the results of many trees to mitigate this issue.

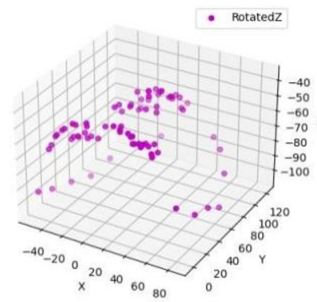
The translated data type, despite being centered around the origin, might introduce a new form of variance that the classifiers need to adjust to, explaining why there's a slight performance drop for all classifiers. However, Random Forest manages to maintain high accuracy due to its inherent mechanism of averaging out decisions from multiple trees, which can handle the variance introduced by translation effectively.

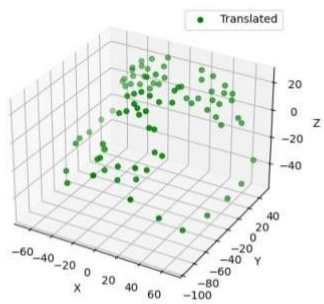
Sample plots for each data type – original, translated, rotated (1 each for x, y, and z):











Confusion Matrices for All Classifiers and Data Types

1. RF Original

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	1012.3	0	0	0	0	0
Disgust	0.1	1017.1	0	0	0	0
Fear	0	0	1004.2	0	0	0
Happy	0	0	0	997.3	0	0
Sad	0	0	0	0	1014.2	0.1
Surprise	0	0	0.2	0	0	994.7

2. RF Rotated X

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	1012.3	0	0	0	0	0
Disgust	0.1	1017.1	0	0	0	0
Fear	0	0	1004.2	0	0	0
Happy	0	0	0	997.2	0	0
Sad	0	0	0	0	1014.2	0.2
Surprise	0	0	0.2	0.1	0	994.6

3. RF Rotated Y

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	1012.3	0	0	0	0	0
Disgust	0.1	1017.1	0	0	0	0
Fear	0	0	1004.2	0	0	0
Happy	0	0	0	997.3	0	0
Sad	0	0	0	0	1014.2	0.1
Surprise	0	0	0.2	0	0	994.7

4. RF Rotated Z

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	1012.2	0	0	0	0	0
Disgust	0.2	1017.1	0	0	0	0
Fear	0	0	1004.2	0	0	0.2
Happy	0	0	0	997.3	0	0
Sad	0	0	0	0	1014.2	0.1
Surprise	0	0	0.2	0	0	994.5

5. RF Translated

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	1011.6	0.7	0.1	0.2	0	0
Disgust	0.5	1015.1	0.3	0.3	0.1	0.7
Fear	0	0.6	1002.7	1	0.1	0.2
Happy	0	0.3	0.9	995.8	0	0.2
Sad	0.2	0.3	0.3	0	1013.8	0.4
Surprise	0.1	0.1	0.1	0	0.2	993.3

6. SVM Original

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	845.3	100.5	49.6	37.8	55.1	32.2
Disgust	44.4	751.1	84.5	25.6	18.6	17.8
Fear	25.8	74.6	653.3	44.6	23.7	32.9
Happy	20.8	37.8	75.5	835	23.5	30.3
Sad	56.9	23.6	53.2	28	870.9	40.9
Surprise	19.2	29.5	88.3	26.3	22.4	840.7

7. SVM Rotated X

	Angry	Disgust	Fear	Happy	Sad	Surprise

Angry	844.5	100.4	49	38.2	55.2	32
Disgust	44.3	751.3	84.5	25.8	18.6	17.9
Fear	26.2	74.4	653	44.2	23	32.6
Happy	20.9	38.1	75.9	834.6	23.7	30.4
Sad	56.9	23	53.8	27.7	871.8	41.4
Surprise	19.6	29.9	88.2	26.8	21.9	840.5

8. SVM Rotated Y

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	845.8	100.3	49.1	37.7	55.6	32.1
Disgust	43.6	751	84.8	25.5	18.7	17.7
Fear	26.1	74.7	652.4	44.6	23.5	32.6
Happy	20.8	38.3	76.6	835.3	23.7	30.3
Sad	56.9	23.4	53.4	27.8	870.3	41.5
Surprise	19.2	29.4	88.1	26.4	22.4	840.6

9. SVM Rotated Z

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	845.2	100.9	49.5	38.0	55.3	32.1
Disgust	44.0	750.6	85.0	25.9	18.5	18.0
Fear	26.1	74.9	652.5	44.6	23.0	32.9
Happy	20.9	37.6	76.4	834.4	23.8	30.2
Sad	57.1	23.4	53.2	27.6	871.4	40.6
Surprise	19.1	29.7	87.8	26.8	22.2	841.0

10. SVM Translated

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	841.8	98.3	50.1	40.0	59.6	29.7
Disgust	45.7	749.5	87.0	25.3	18.2	19.6
Fear	23.4	72.3	645.2	42.9	28.2	34.1
Happy	20.5	38.1	81.7	836.3	20.7	34.3
Sad	60.7	27.1	53.8	25.8	867.2	48.8
Surprise	20.3	31.8	86.6	27.0	20.3	828.3

11. TREE Original

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	999.4	4.8	2.6	2.4	1.7	1.9
Disgust	3.3	997.7	5.1	1.9	1.4	5.2
Fear	2.6	4.9	984.7	3.9	1.6	5.3

Happy	2.3	3.2	5.4	982.8	1.9	3.8
Sad	2.4	2.9	2.2	2.9	1005	4.3
Surprise	2.4	3.6	4.4	3.4	2.6	974.3

12. TREE Rotated X

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	998.7	4.6	1.8	1.7	2.5	1.9
Disgust	3.9	999.3	5.4	3.0	1.4	3.4
Fear	3.0	3.9	986.1	4.0	1.8	5.4
Happy	1.5	3.0	4.1	983.5	1.9	4.0
Sad	3.0	2.7	2.6	2.5	1004.3	4.0
Surprise	2.3	3.6	4.4	2.6	2.3	976.1

13. TREE Rotated Y

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	999.4	4.2	2.8	1.7	2.0	2.4
Disgust	3.5	998.9	4.4	3.0	1.3	4.7
Fear	2.8	5.1	984.4	4.1	2.1	6.3
Happy	2.0	3.1	5.1	983.4	2.4	3.4
Sad	2.7	1.7	2.3	2.7	1003.9	4.2
Surprise	2.0	4.1	5.4	2.4	2.5	973.8

14. TREE Rotated Z

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	1001.2	3.4	2.0	1.7	1.9	2.3
Disgust	3.2	1000.3	4.7	2.2	1.4	4.7
Fear	2.4	4.2	986.1	5.4	1.9	5.2
Happy	1.8	3.0	4.9	982.8	2.4	3.2
Sad	1.8	2.3	2.3	3.2	1003.4	4.5
Surprise	2.0	3.9	4.4	2.0	3.2	974.9

15. TREE Translated

	Angry	Disgust	Fear	Happy	Sad	Surprise
Angry	976.3	10.9	7.1	5.7	7	6.5
Disgust	10.4	972.8	10.9	8	5.6	8.8
Fear	6.2	11.7	954.2	13.3	6.5	15.9
Happy	6	9.9	12.5	956.8	5.4	8.3
Sad	8.4	4.8	8.4	6.2	981.2	8.2
Surprise	5.1	7	11.3	7.3	8.5	947.1