



# FACIAL EMOTION CLASSIFICATION USING SEMI-SUPERVISED LEARNING

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## ABSTRACT

Facial emotion classification aims to classify facial expressions into emotional states, which is essential for non-verbal communication. Despite its significance, facial emotion classification remains a challenging task due to factors like facial occlusion, lighting variations, and non-frontal head poses. This research explores the enhancement of facial emotion classification by integrating deep learning models, specifically convolutional neural networks (CNNs), with semi-supervised learning techniques such as FixMatch. By leveraging both labeled and unlabeled data, our approach improves classification accuracy in real-world settings. Applications of this work extend across human-computer interaction, psychology, marketing, and security, contributing to more intuitive and responsive systems.



## DATASET

- We used a FER2013 dataset which consists of 35,887 images from github.
- github. Resolution: 48x48 pixels gray scale images.
- Split training dataset into labeled (30%) and unlabeled (70%) subsets
- Label images - 8612, Unlabeled images - 20,097
- Github Link :- <https://github.com/parth1620/Facial-Expression-Dataset> [2]

Summary of the Dataset

TABLE I: Number of data in the FER-2013 dataset

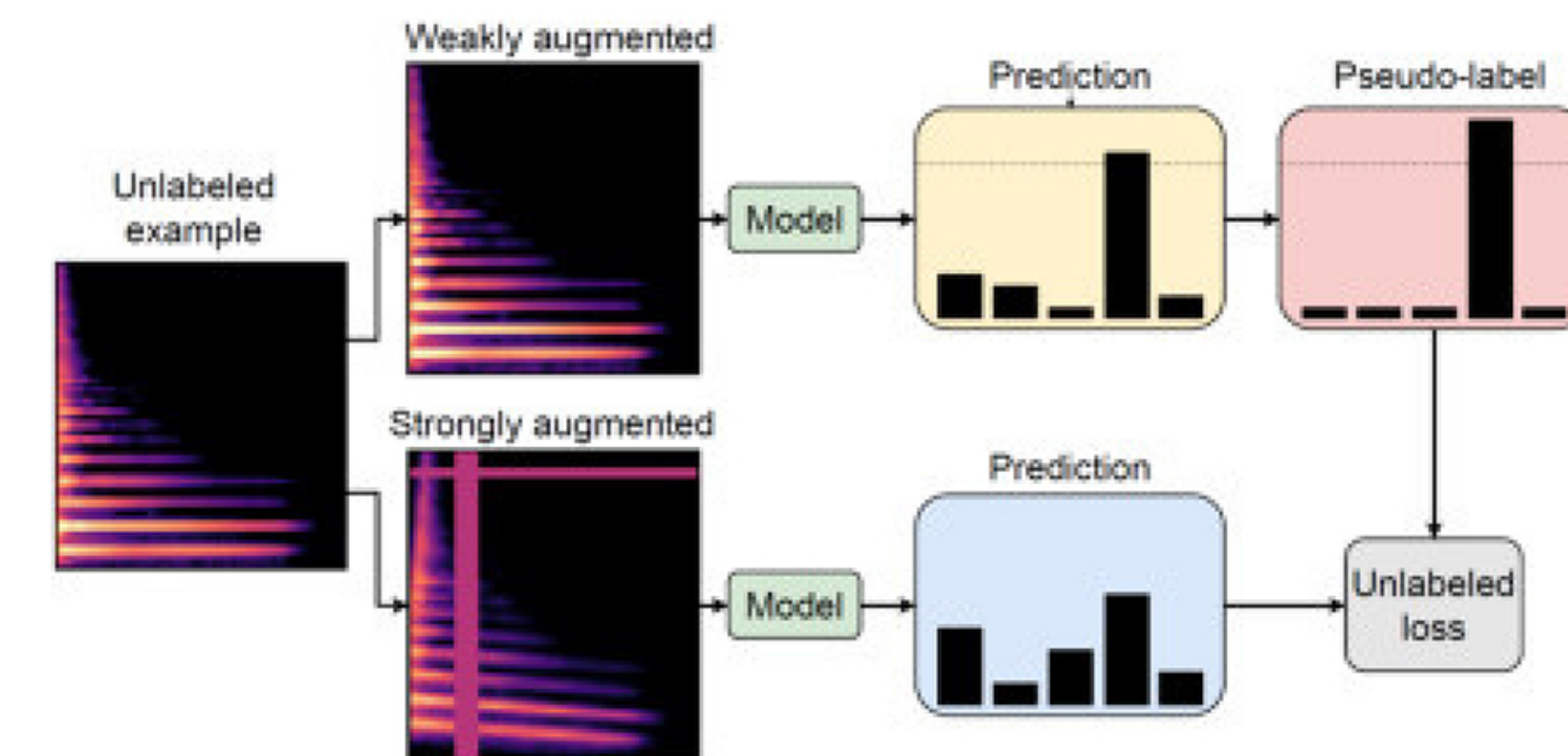
micro-expression (Classification)	Validation Data		Training Data	Dataset Total
	Public	Private		
Angry	467	491	3995	4953
Disgust	56	55	436	547
Fear	496	528	4097	5121
Happy	895	879	7215	8989
Sadness	653	594	4830	6077
Surprise	415	416	3171	4002
Contempt	607	626	4965	6198
	3589	3589	28709	35887

Samples of the dataset images [3]



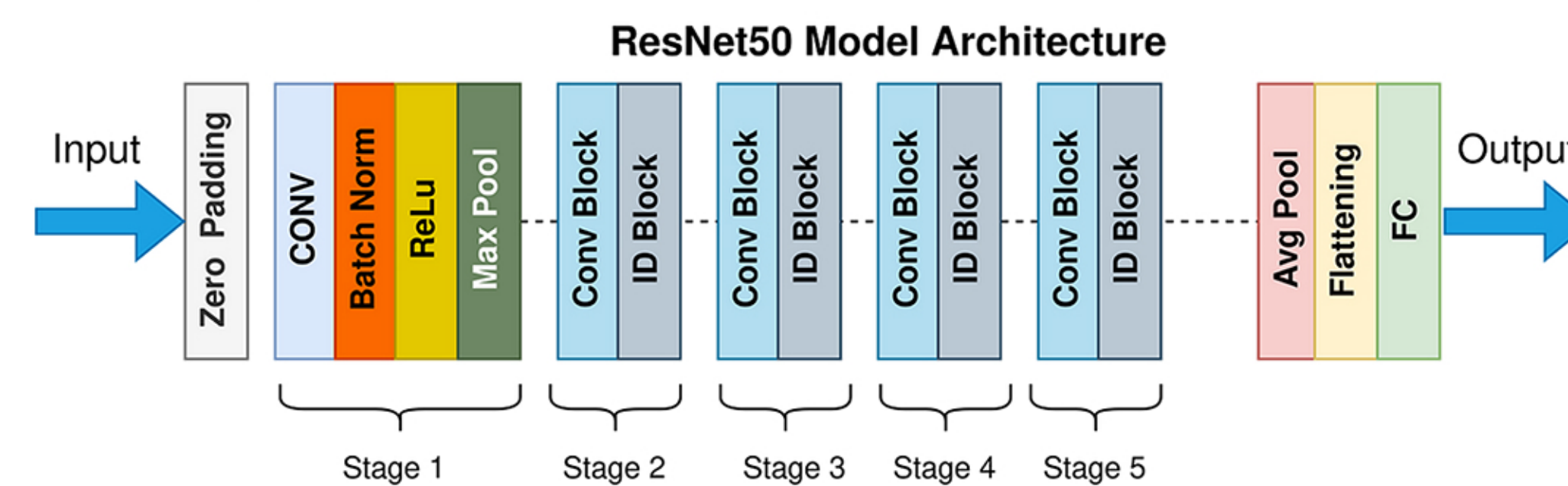
## METHODOLOGY

- This research focused on improving facial emotion classification using a semi-supervised learning approach. The **FixMatch** algorithm was utilized, which leverages both labeled and unlabeled data to enhance model performance.
- We used **ResNet50 architecture** which is a deep convolutional neural network (CNN) known for its residual blocks, allowing for efficient training of very deep networks by bypassing gradient vanishing issues through shortcut connections.



FixMatch Algorithm

- ResNet50 consists of 50 layers, including convolutional, pooling, and fully connected layers, and it can model complex patterns in data, making it suitable for facial emotion classification. [4]



Equations

- Supervised Loss:** This is the standard cross-entropy loss applied to labeled data: [5]

$$L_{sup} = - \sum y_i \log(\hat{y}_i)$$

- Consistency Loss:** This enforces consistency between the pseudo-labels from weakly augmented images and predictions from strongly augmented images:

$$L_{unsup} = \frac{1}{|U|} \sum_{u \in U} 1(\max(p(u^w)) \geq r) \cdot H(\hat{p}(u^s), \hat{p}(u^w))$$

- Total Loss:** The overall loss function is a combination of both supervised and unsupervised loss:

$$L = L_{sup} + \lambda L_{unsup}$$

## EXPERIMENTAL SETUP

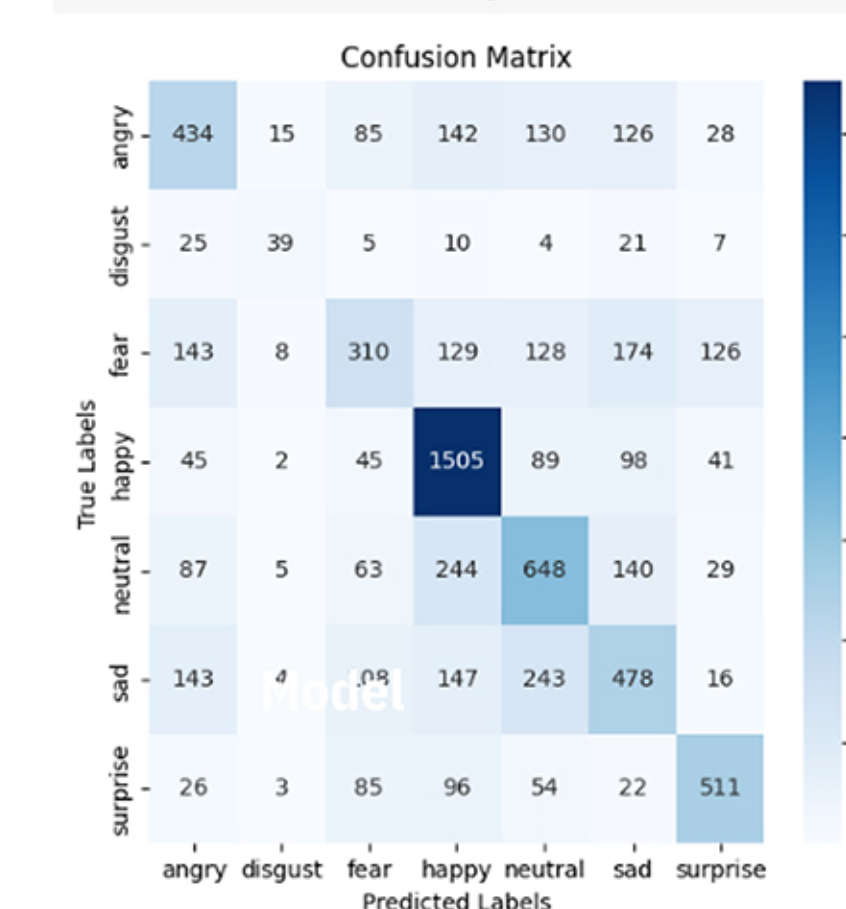
- Hyperparameters**
  - Learning rate - 0.001
  - Batch size - 32
  - Epochs - 30
  - Model - ResNet50
  - Confidence Threshold - 0.95
- Data Augmentation**
  - Random Resize Crop: 224
  - Random Horizontal Flip
  - Normalization: [0.485, 0.456, 0.406], [0.229, 0.224, 0.225]

## RESULTS

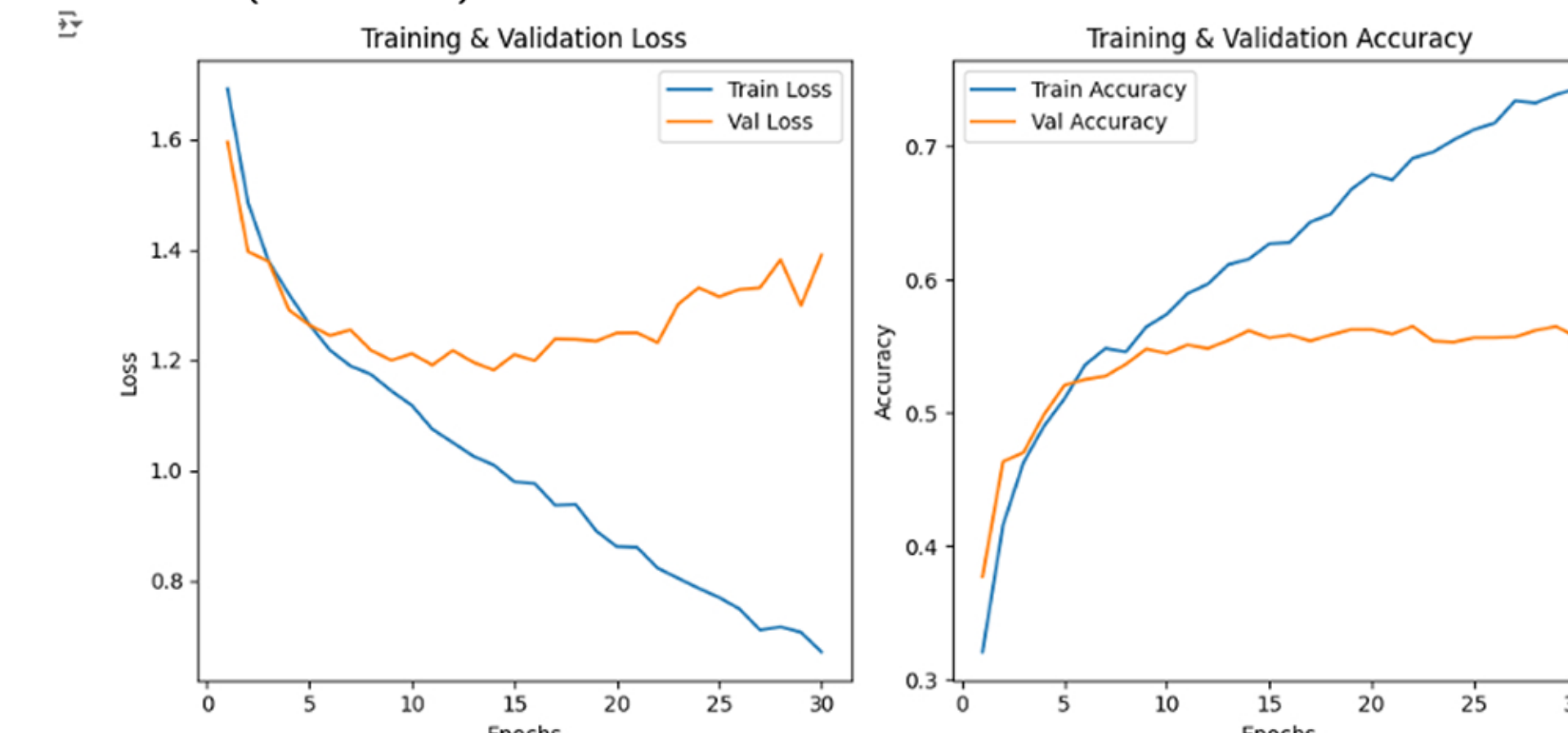
- Comparison with previous research models

	Method	Architecture	Accuracy
My Results	FullySupervised	ResNet50	64.18%
	FixMatch	ResNet50	56.21%
Previous Results	FullySupervised[1]	ResNet18	64.57%
	FixMatch [1]	ResNet18	59.46%

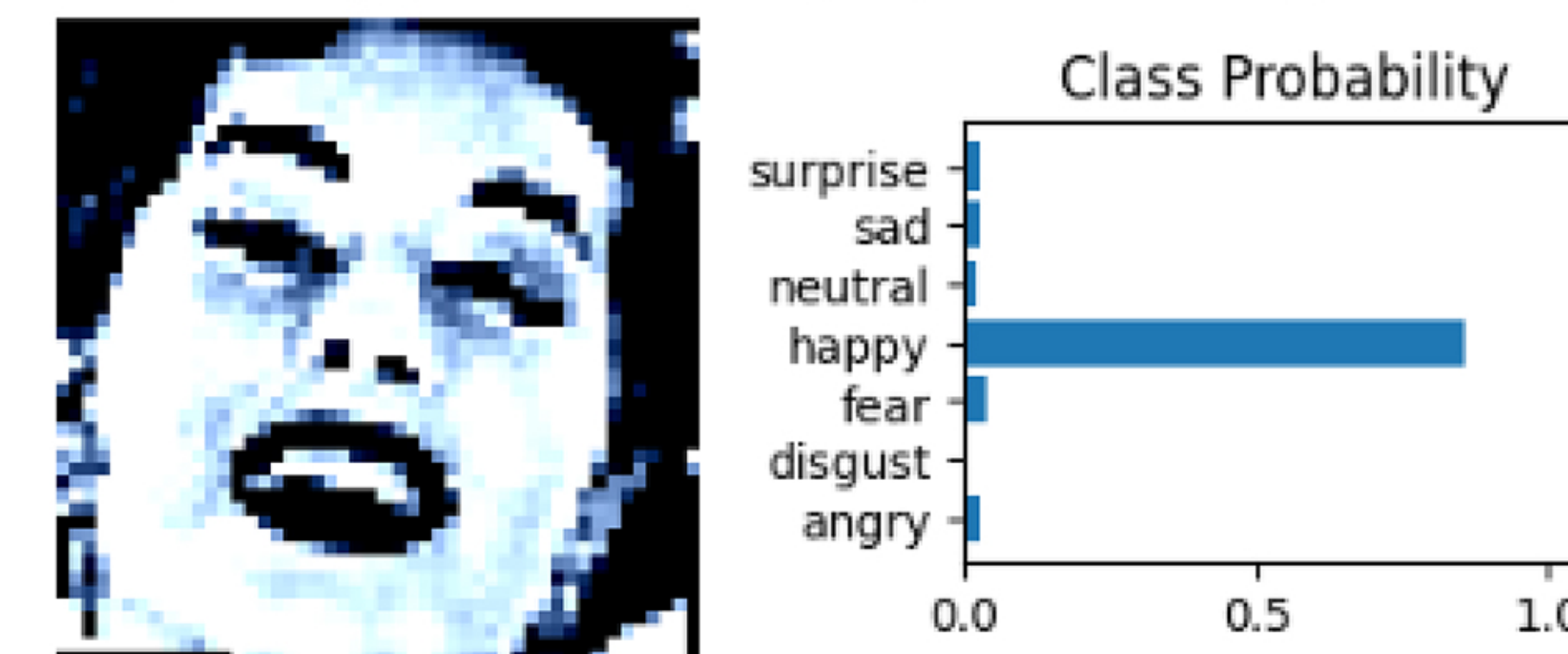
- Confusion matrix for semi-supervised learning (FixMatch):



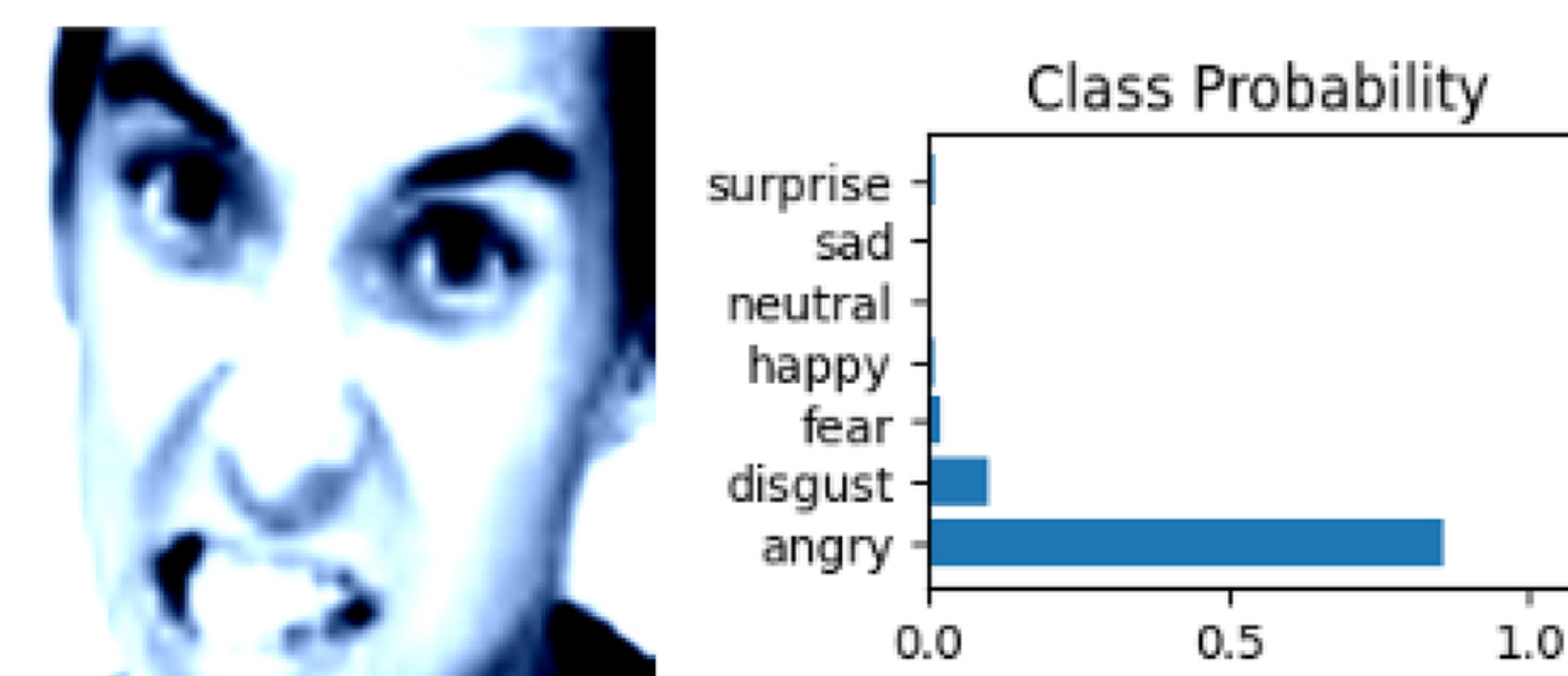
- Loss & Accuracy versus epoch for semi-supervised learning (FixMatch):



- Sample image prediction for fully-supervised learning:

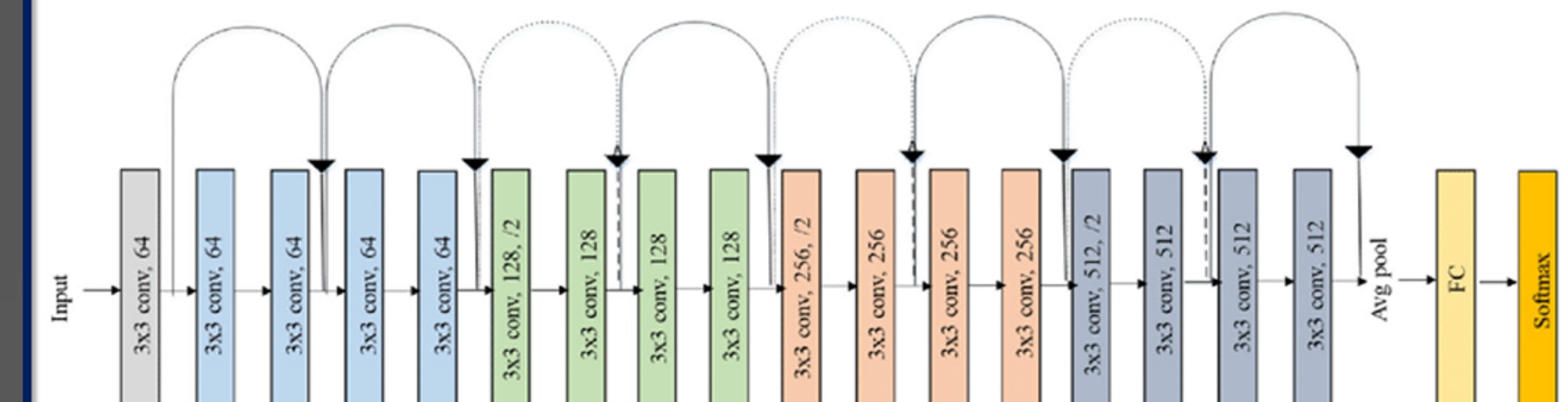


- Sample image prediction for semi-supervised learning (FixMatch):



## DISCUSSION

- In this study, we explored the application of ResNet50 with FixMatch for facial expression classification, building on previous research that used ResNet18.
- While ResNet50, a deeper architecture, was expected to improve performance, our results did not surpass those of ResNet18, potentially due to overfitting or the increased complexity of the model.
- Despite this, the application of FixMatch for semi-supervised learning allowed us to effectively utilize unlabeled data.



- One challenge we encountered was the inherent complexity of facial expression classification, especially when dealing with facial occlusions and non-frontal head poses. This suggests that further refinement of ensemble methods or more robust augmentation techniques could enhance the accuracy of facial emotion classification models.
- Future work should also address the limitations of semi-supervised learning approaches in handling diverse real-world data.

## CONCLUSION

- Previous research used ResNet18, while this study applied ResNet50 to explore performance improvements.
- ResNet50 initially yielded lower accuracy than the previous ResNet18 results.
- Future work could explore ensemble techniques or other advanced methods to further enhance accuracy and address the performance gap between ResNet50 and ResNet18. Additionally, experimenting with larger datasets or alternative architectures may yield better results.

## REFERENCES

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- Jaiswal, A., Raju, A. K., & Deb, S. (2020). Facial emotion detection using deep learning. In international conference for emerging technology, pp.1-5.
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