SOP Report

Reinforcement Learning Based Online Active Learning to Reduce Annotation Effort

Under the guidance of

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Prepared by-

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1 Introduction

Human Activity Recognition (HAR) models are essential for various applications, including health monitoring and daily living assistance. However, obtaining ground truth labels for training these models is often challenging, mainly when relying on external annotators. To address this challenge, this project introduces Reinforcement Learning Based Online Active Learning (ROAR), an innovative approach that combines Reinforcement Learning (RL) with online active learning for HAR. ROAR leverages the sequential nature of HAR data streams to make intelligent query decisions, optimising human-provided annotations and enhancing HAR model performance. In this project, we evaluated the performance of ROAR in various datasets in comparison to other baseline methods, including supervised learning, active learning, and leave-one-subject-out (LOSO) validation.

2 Case Studies

2.1 Emotion Detection

The dataset comprises transition probabilities between emotional states labelled as Relaxed, Stress, Happy, Sad, and Mean, along with session duration, session length, and the presence of special characters for 32 users. Based on these given features, the aim is to predict emotion of the user. A Random Forest model is used to implement baselines and the ROAR algorithm. The Leave One Sample Out method performs the best, with an F1 score of 87.3. However, more sample data from other users is required before the model can be trained. ROAR provides a better alternative in this case. It outperforms supervised and active learning baselines with an F1 score of 83.9.

Additionally, ROAR achieves a significant 54.57% reduction in probe rate, compared to a 40.83% reduction with Active Learning. However, when we update transition probability features based on our earlier predictions in the case of mod_ROAR, there is a significant drop in the F1 score. This drop results from the model predicting wrong results, which are then considered and used to update the transition probabilities features.

ROAR parameters -

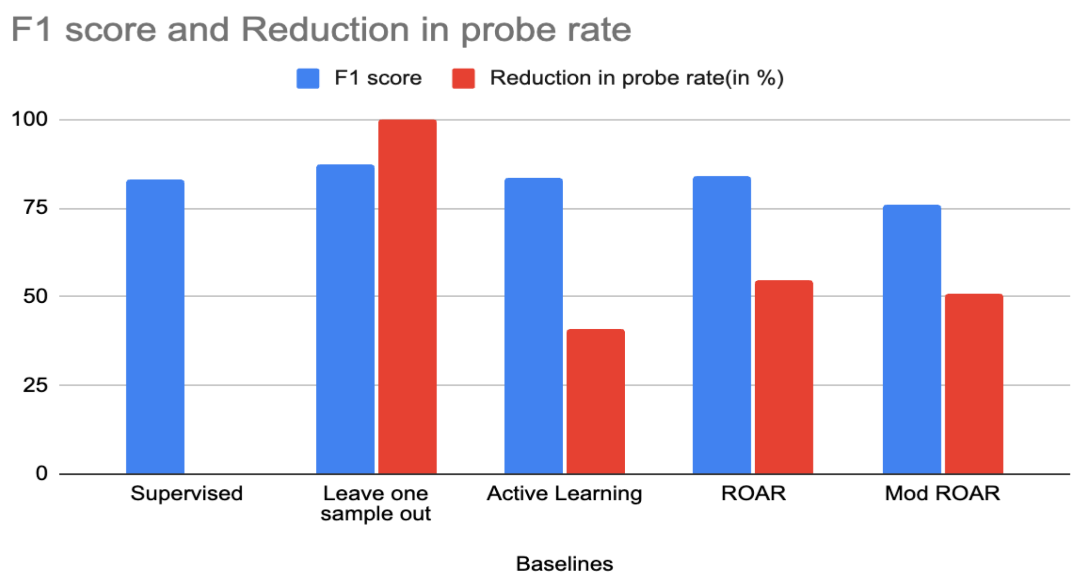
Epsilon = 0.35

Threshold = 0.7

Learning Rate = 0.01

Positive Reward = 1.0

Negative Reward = 2.0



2.2 CASE dataset

This dataset consists of data from 30 users, each with 243 records. Features such as 'Score', 'arousal_acc_video', 'valence_acc_video', and 'GSR_Diff' were used for a binary classification problem. To address the imbalanced nature of the dataset, Logistic Regression was chosen as the base model, as Tree-Based Classifiers are generally biased toward the class with a more significant number of instances. Additionally, the “class_weight” hyperparameter was set to "balanced," samples with a probability of classifying as 1 >0.3 were labelled as 1 to handle the imbalanced dataset.

While considering other baselines, such as Active Learning, with 40% of data from each user pooled to create a base learner for each user, resulted in a high False Positive Rate (FPR) of 0.36 with no significant improvement in True Positive Rate (TPR). Similarly, the Leave One Sample Out baseline yielded an FPR of 0.29. Hence, these baselines are not included in further analysis.

For ROAR, the initial 20% of data was used to train the initial base learner, followed by the next 60% to opportunistically train the model, leaving the remaining 20% for testing.

Comparing Supervised Learning, Active Learning(when data is not pooled), and ROAR reveals notable performance metrics differences. While all three methods exhibit similar

Mean F1 Scores, with Supervised Learning at 0.806, Active Learning at 0.8, and ROAR at 0.804, ROAR outperforms Active Learning in Mean True Positive Rate (TPR) with a score of 0.818 compared to Active Learning's 0.798. These results indicate that ROAR offers improved F1 Score and TPR performance compared to Active Learning, although Active Learning achieves a more significant reduction in probe rate.

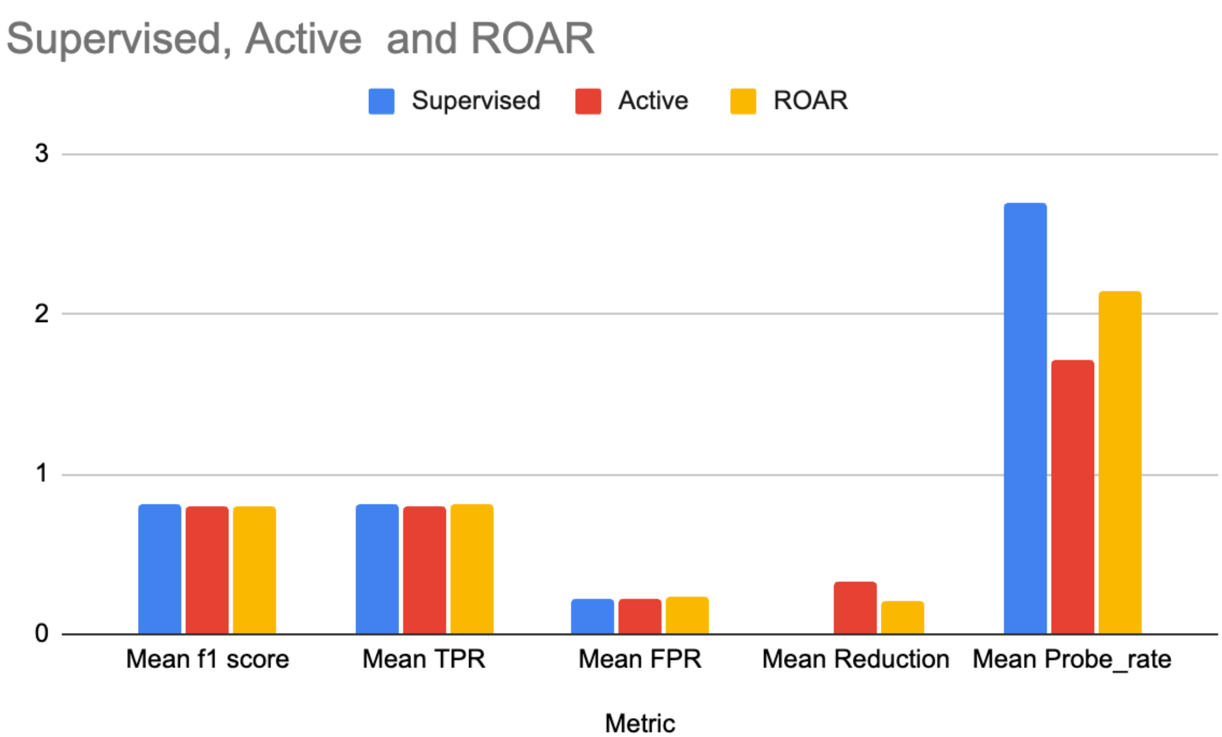
ROAR parameters -
Epsilon = 0.7

Threshold = 0.1

Learning Rate = 0.1

Positive Reward = 1.0

Negative Reward = 2.0



2.3 K-emocon dataset

This dataset comprises data from 32 users, with an average of 208 records per user.
For a binary classification problem, features including 'Score', 'EDA_diff', 'HR_diff', 'TEMP_diff', and 'BVP_diff' were selected from the dataset.
For ROAR, the initial 20% of data was used to train the initial base learner, followed by the next 60% to opportunistically train the model, leaving the remaining 20% for testing.
All methods achieved high Mean F1 Scores. ROAR ans Supervised Learning outperformed other methods, achieving the highest Mean F1 Score at 0.98, while Active Learning (not Pooled) closely followed with scores of 0.97. ROAR exhibited the lowest Mean False Positive Rate (FPR) at 0.02. It demonstrated the highest Mean Reduction in the probe rate at 0.56 (excluding leave-one-sample-out), indicating its robust performance in accurately identifying positive instances and reducing unnecessary probe rates.

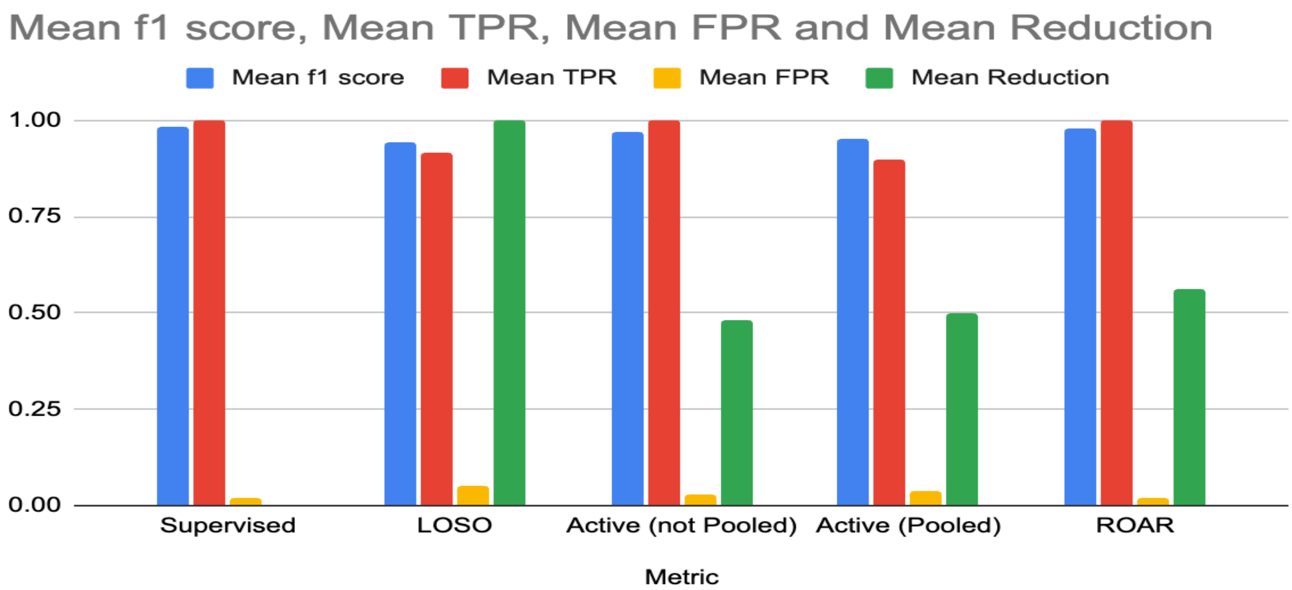
ROAR parameters -
Epsilon = 0.2

Threshold = 0.6

Learning Rate = 0.05

Positive Reward = 1.0

Negative Reward = 2.0



2.4 User study (36 users)

This dataset consists of data from 36 users, each with an average of 239 records. Features such as 'Score', 'GSR_diff', 'HR_diff', 'valence_acc_video', and 'arousal_acc_video' were used for a binary classification problem. To address the imbalanced nature of the dataset, Logistic Regression was chosen as the base model, as Tree-Based Classifiers are generally biased toward the class with a more significant number of instances. Additionally, the "class_weight" hyperparameter was set to "balanced," samples with a probability of classifying as 1 >0.3 were labelled as 1 to handle the imbalanced dataset.

While considering other baselines, such as Active Learning, with 40% of data from each user pooled to create a base learner for each user, resulted in a high False Positive Rate (FPR) of 0.38 with no significant improvement in True Positive Rate (TPR). Similarly, the Leave One Sample Out baseline yielded an FPR of 0.34. Hence, these baselines are not included in further analysis.

For ROAR, the initial 10% of data was used to train the initial base learner, followed by the next 70% to opportunistically train the model, leaving the remaining 20% for testing.

On comparison with the baseline, we find that while all three methods demonstrate high Mean F1 Scores, with Supervised Learning and ROAR achieving the highest at 0.859, ROAR also outperforms Active Learning in Mean True Positive Rate (TPR) with a score of 0.957 compared to Active Learning's 0.942. Additionally, ROAR exhibits the lowest

Mean False Positive Rate (FPR) at 0.181, indicating its superior ability to avoid misclassifications. Moreover, ROAR demonstrates a significant reduction in the mean probe rate, achieving 2.48, compared to Active Learning's 2.579, highlighting its efficiency in reducing human annotation effort.

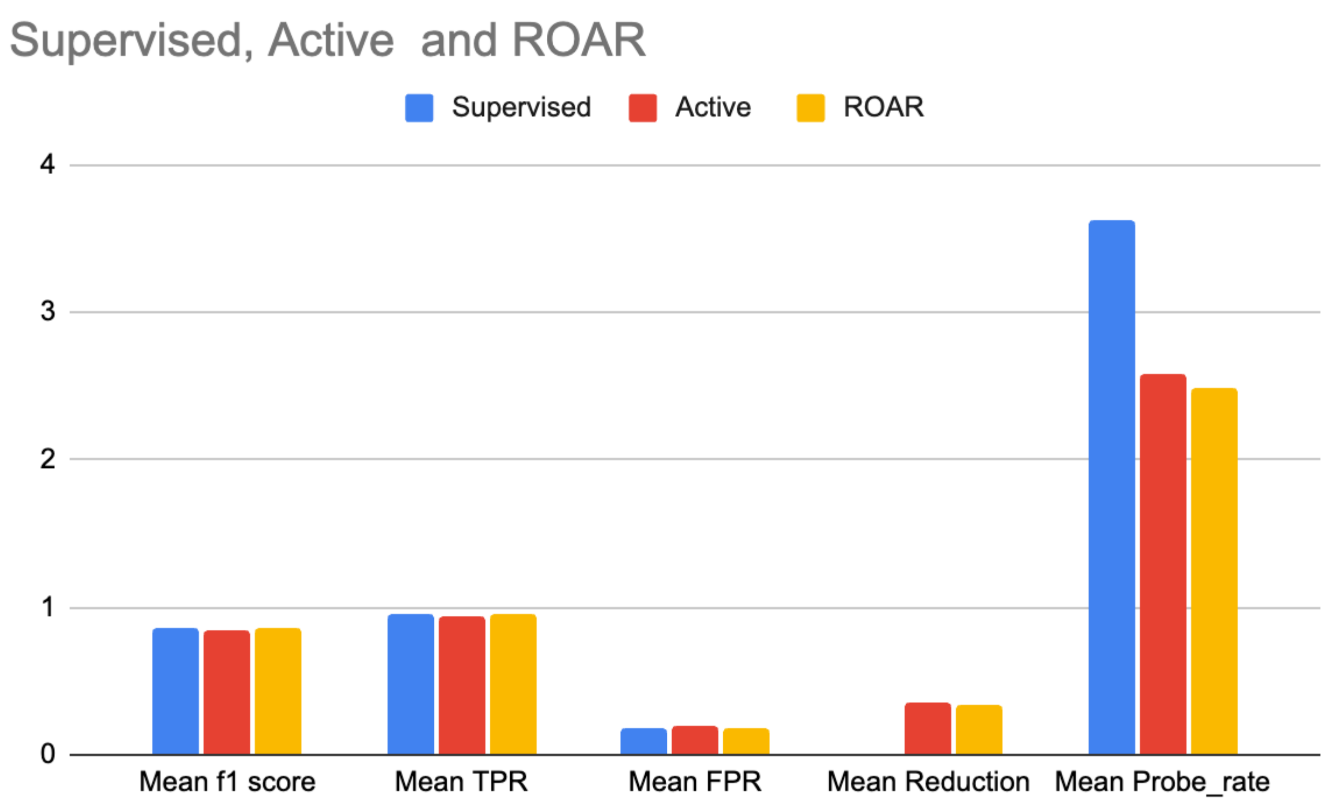
ROAR parameters -
Epsilon = 0.6

Threshold = 0.9

Learning Rate = 0.2

Positive Reward = 1.0

Negative Reward = 2.0



Conclusion

In this study, we introduced Reinforcement Learning Based Online Active Learning (ROAR) as an innovative approach to reduce human annotation effort in Human Activity Recognition (HAR) systems. By combining Reinforcement Learning (RL) with online active learning, ROAR leverages the sequential nature of HAR data streams to make intelligent query decisions, optimising human-provided annotations and enhancing HAR model performance.

We demonstrated ROAR's superiority over baseline methods through case studies on various datasets. With comparable or higher F1 scores and True Positive Rates (TPR) and lower False Positive Rates (FPR) than supervised learning baselines, ROAR showcases its ability to identify human activities while minimising misclassifications accurately. ROAR significantly reduces the mean probe rate, highlighting its efficiency in minimising human annotation effort while maintaining high classification accuracy.

Future research could focus on enhancing ROAR's performance with larger datasets and exploring its applicability in real-world scenarios. Further investigation into ROAR's scalability, adaptability to different sensor modalities and environments, and computational efficiency could enhance its usability and impact in various HAR applications. Additionally, exploring ROAR's potential in improving the quality of life for individuals, enhancing healthcare monitoring systems, and optimising industrial processes could pave the way for more efficient and accurate HAR systems. In conclusion, ROAR presents a promising approach to reducing human annotation effort in HAR systems, offering potential benefits in accuracy, efficiency, and real-world applicability.

Detailed data and results for each dataset analysed in this study can be accessed by clicking the links below.

ROAR emotion detection

ROAR (other datasets)

The implementation of ROAR and other baseline methods for the datasets analysed in this study can be found on GitHub. Click the link below to access the implementation details:

Github