Department of Mechatronics & Industrial Engineering

Chittagong University of Engineering and Technology

ACTIVE ONE-SHOT LEARNING FOR PERSONALIZED HUMAN AFFECT ESTIMATION

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SUPERVISED BY:

<SUPERVISOR NAME>

<DESIGNATION>

DEPARTMENT OF MECHATRONICS & INDUSTRIAL ENGINEERING

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Declaration (Font 16)

(**Times New Roman, Font 12, line spacing 1.5**) This thesis proposal is a presentation of our original research work ideas. Whenever contributions of others are involved, every effort has been made to indicate this clearly, with due reference to the literature, and acknowledgement of collaborative research and discussions.

This work was done under the guidance of Professor [supervisor's name], at Chittagong University of Engineering and Technology, Chittagong.

[Candidates name and signature]

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Abstract (Font 16)

(**Times New Roman, Font 12, line spacing 1.5, Full justification**) Building models that can classify human affect leads to the challenge of learningon data that is complex in features and limited in size and labels. How can thesemodels balance being general and personalized, capturing both the commonalitiesand the individual quirks of people? While previous research has explored the inter-section of deep learning, active learning, and one-shot learning to craft models thatare semi-supervised and data-efficient, these methods have not yet been examined inthe context of personalized affective computing. This study presents a novel activeone-shot learning model for personalized estimation of human affect, in particular,detection of pain from facial expressions. The model demonstrates the ability tolearn an active learner that achieves high accuracy, learns to become data efficient,and introduces model personalization to match or outperform fully supervised andpopulation-level models (Do not use abbreviations or insert tables, figures or references into your abstract. Your abstract generally should not exceed about 300 words.)

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Acknowledgement (Font 16)

(**Times New Roman, Font 12, Line spacing 1.5, Full justification**) Above all, I would like to express my gratitude to my supervisor <**supervisor’s name**> for accepting me into his research group and also express my heartfelt thanks to him for his guidance, encouragement and continuous support during my graduate studies. His enthusiasm for teaching and research offered challenging opportunities to expand my scientific knowledge and my growing interest in the world of Mechatronics.

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LIST OF SYMBOLS AND ABBREVIATIONS

SYMBOLS

f	Frequency
λ	Wave length
c	Velocity

ABBREVIATIONS

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Chapter 01

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Introduction

1.1 Motivation[Front 12]

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[Times New Roman, Font 12, Line spacing 1.5] Emotions in humans are often likened to colors. Each is meaningful in context,difficult to describe, and experienced differently by each person. Still, humans havefound ways to identify their own emotions, recognize emotions in others, and sharea common language for a wide range of nuanced emotions. Machines, on the otherhand, struggle with this difficult task. Of the next major challenges in artificialintelligence (AI), one is to capture the emotional intelligence that humans learn overtheir lifetimes. Today's voice assistants like Apple's Siri and conversational chatbotslike Woebot [5] cannot yet understand in depth the emotions a person might beexpressing in conversation. For Al to better serve humans and for humans to betterunderstand themselves, machines should build understanding of human emotion, oraffect, and learn how to best respond to people given their affective state.One of the central challenges of affective computing is to study and characterizeaspects of human affect quantitatively [23]. As the mechanisms of human affect arepoorly understood, deep learning models may help us to find promising signals thatare most associated with affect, for example, examining features from human facialand physiological data to study subtle human emotions. However, typical deep learn-ing algorithms are extremely data-hungry, requiring many data points and human-provided labels to perform supervised training. This training paradigm isn't feasiblefor many human affective datasets which are often limited in size and costly to la-bel. Furthermore, with affect data, rather than employing a "one-size-fits-all" model an ideal personalized affect model would be able to provide accurate estimates forindividuals, while maintaining a generalized model that can be applied across thepopulation. This personalized machine learning paradigm has been previously ap-plied to affective computing [91, and will be expanded in this work.To reduce deep learning models' data consumption while maintaining high modelperformance, many methods have been developed in

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active learning. Recent workdemonstrates the ability of active one-shot learning to train a model to perform clas-sification while balancing accuracy and data consumption [39]. This thesis builds onthe active one-shot learning model and presents a novel personalized active learning model for human affect estimation, particularly applied to pain detection through fa-cial expressions. The personalized active learning model can learn to learn efficiently,while achieving high accuracy on a population and individual level. The work pre-sented in the following thesis does not claim to outperform existing models in affectestimation, but examines how personalization and active learning can bolster currentaffect estimation models, an intersection of research areas that is just beginning to be explored.

1.2 Thesis Objectives

1.3 Thesis Overview

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Chapter 02

Literature Review

2.1. Introduction

2.2 Affect Estimation

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One focus of affective computing research has been to create computational modelsand concrete metrics of affect in humans [23]. Much previous work has applied deeplearning to learn supervised models of affect through facial [11] and physiologicaldata [20]. These works demonstrate the potential for deep neural networks to processcomplex data and to detect important features associated with human affect. For anextensive overview of existing efforts in automated affect analysis, see work by Zeng,et. al. [42].A residual issue in applying deep learning to affect estimation is the lack of dataefficiency. As the next section explores, active learning may prove to be a promisingsolution to creating more data-efficient classification models.

2.3 Active Learning Framework

Often for affect datasets, obtaining large, labeled datasets is time-consuming andcostly. In these settings, active learning can be employed to learn more effectively onthe data available, without requiring the model to see the label for every data point.Active learning is a semi-supervised machine learning method often applied tosettings in which there is a large set of unlabeled data, for which one would like to learn the true labels, and a small set of labeled data on which the active learningmodel can train [30]. In this framework, the model trains on the small set of labeleddata to make an informed prediction on the unlabeled data. If the model is uncertainenough about the label of the input data, it can query an oracle which will returnthe true labels of the data. Otherwise, the model continues receiving new data,for which it repeats the same labeling process. In the active learning setting, it isassumed that requesting labels for data is costly; thus, the model wants to limit

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thenumber of times that it requests labels from the oracle. In classification settings,from estimation of facial action unit labels [361 to discovering feature artifacts inelectrodermal signals 1401, active learning has been found to train models on a smallerfraction of the training set, while maintaining a similar accuracy as models trainedin a fully supervised setting.

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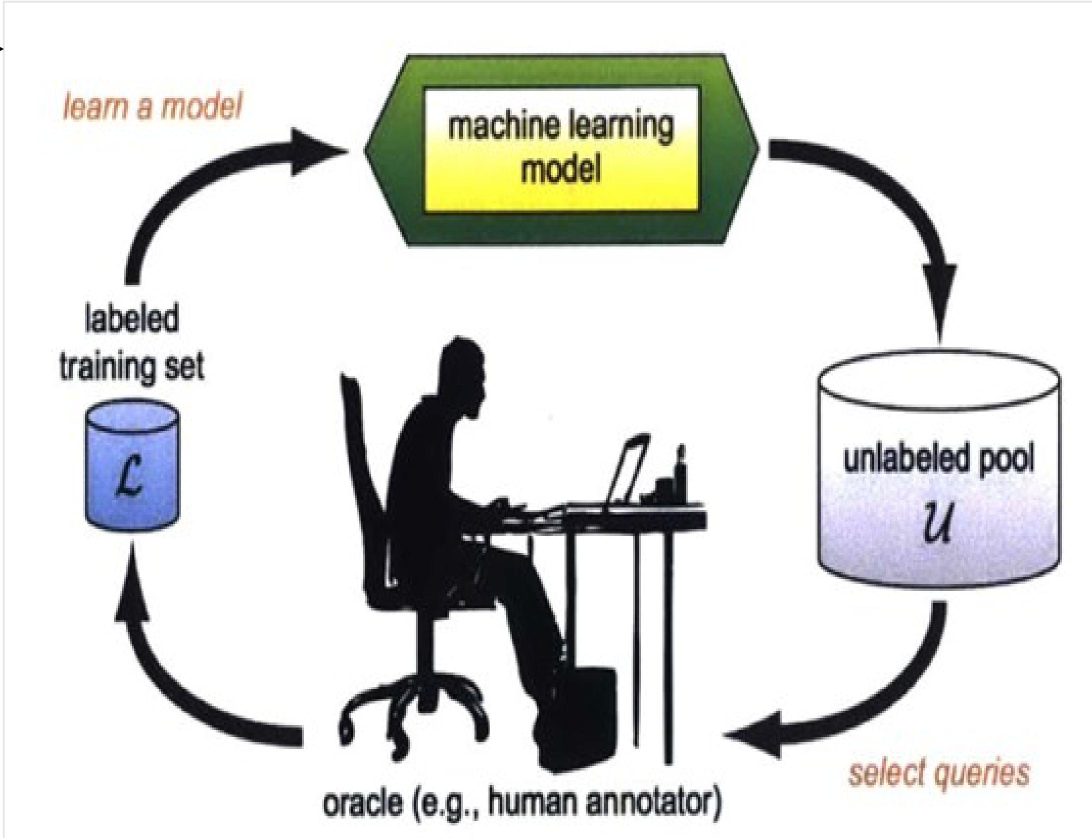

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Figure 2.1: The general active learning framework.

2.4 Conclusion

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Chapter 07

Conclusion

This work contributes a novel active one-shot learning learning model that learns to build a personalized active learner that balances learning general and personalized information for human affect data. As demonstrated on the UNBC-McMaster shoulder pain dataset, this meta learning model learns how to actively learn and how to decrease the model's need for labels, while achieving accuracies near to that of a supervised model. By personalizing the model on a subset of the target population, the model achieves even higher accuracy and lower requests on held out data from the target population.

Ideally, the social bots of the future will contain personalized active learning models that can interact with people while processing the context and data signals from the humans in the interaction in an automatic and data-efficient manner. As humans are creatures of emotion, our technology should be able to understand the rich palette of affective states that humans express and perhaps, in turn, help us better understand ourselves.

REFERENCES

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Appendix-A

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Table A.1: Main experiment functions and their description

Function	Description
get-episode	Samples one episode of data with one patient.
get-model-performance	Analyzes model output and performance metrics.
make-data arrays	Creates train and validation datasets for later sampling.
rundatabatch	Collects a batch of data and runs the batch through the model.
run-supervised-test	Trains a supervised model and saves the model performance.
save-requested-data	Saves data points whose labels were requested by the training model.