A Brief Survey of Machine Learning Methods for Emotion Prediction using Physiological Data

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**Abstract**—Emotion prediction is a key emerging research area that focuses on identifying and forecasting the emotional state of a human from multiple modalities. Among other data sources, physiological data can serve as an indicator for emotions with an added advantage that it cannot be masked/tampered by the individual and can be easily collected. This paper surveys multiple machine learning methods that deploy smartphone and physiological data to predict emotions in real-time, using self-reported ecological momentary assessments (EMA) scores as ground-truth. Comparing regression, long short-term memory (LSTM) networks, convolutional neural networks (CNN), reinforcement online learning (ROL), and deep belief networks (DBN), we showcase the variability of machine learning methods employed to achieve accurate emotion prediction.

We compare the state-of-the-art methods and highlight that experimental performance is still not very good. The performance can be improved in future works by considering the following issues: improving scalability and generalizability, synchronizing multimodal data, optimizing EMA sampling, integrating adaptability with sequence prediction, collecting unbiased data, and leveraging sophisticated feature engineering techniques.

**Index Terms**—Emotion regulation, physiological, Machine learning models, EMA, Adaptive models, spatiotemporal data, multimodal

I. **INTRODUCTION**

Emotion recognition (ER) is a sub-field of affective computing that was proposed by Rosalind Picard in 1997 [1]. Affective computing, derived from the word ’affect’ or ’emotion’, is computing that relates to, arises from, or influences emotions. The field spans quantification, modeling, estimation and prediction of human emotional state, and integrating it into a computer system to enable the machine to make affect-aware decisions. In this paper, we will conduct a literature review of emotion prediction only. This paper will not only provide an in-depth survey of the state-of-the-art methods for emotion prediction but also serve as a primer on this topic.

**A. What is emotion?**

Paul Ekman identified seven universal emotions in terms of which all other compound emotions can be defined: happiness, sadness, surprise, fear, anger, disgust, and contempt [2]. Please note that these are all abstract terms, and it is a huge challenge to quantify them. Each individual feels emotions in a different way and currently there’s no central metric to calibrate each individual’s emotion to a standard scale. Many models have been proposed in literature to quantify emotion.

Two main models/techniques that we encountered in literature on emotion prediction are Geneva Emotion Wheel (GEW) [3] and Ecological Momentary Assessments (EMA).

GEW explains emotions in a 2D space defined by valence on one axis and arousal on the other, as shown in Fig. 1. Theoretically, arousal and valence both take continuous values. However, since these values are determined by users, in most experiments these scales are discretized uniformly between 1 and 10.

Ecological momentary assessment (EMA) scores are used as a measure of the dimensions of mental health in the moment that the survey is recorded. For the CrossCheck dataset in particular, it serves as ground truth for the prevalence of schizophrenia symptoms. The survey used for that particular dataset is comprised of 10 one-sentence questions about the current wellbeing of the participant to which they reply a number 0-3 based on the dimension of that aspect of their wellbeing. The number and type of questions are a design choice. This choice trades off between user’s convenience and amount of information.

**B. How is emotion measured?**

After modeling the emotion, the next important question is how it can be measured in terms of more quantifiable...
and easily accessible data sources. This is where learning
comes into the picture and the active research transitions from
psychology to engineering. Before we discuss the learning
methods, it is important to discuss sources of data that are
utilized to learn about emotion.

There are two main categories of data: non-physiological
and physiological. The former mainly is comprised of two
subcategories. The first one is facial expression, text, and
speech, which are captured through images and video. The
second subcategory is movement and gesture, which could
be captured by IMU sensors and GPS. We grouped these
signals together under of the umbrella of non-physiological
signals because the user has a control over them and can
modify/mask them. For example, a person can be angry but
still be able to control their facial expressions in order to not
show it. However, they can not control their physiological
signals, which are comprised of the following:

- Electroencephalography (EEG), which measures brain
  activities
- Electrodermal Activity (EDA), which measures electrical
  conductivity or skin conductance
- Electrooculogram (EOG), which measures eye move-
  ments
- Electrocardiogram (ECG), which measures heart beats

In this paper, we will focus on physiological signals only.

II. MACHINE LEARNING METHODS

After briefly describing emotion and its data sources, now
we will discuss the common machine learning methods that
are used for emotion prediction. Some methods, like rein-
forcement online learning and deep belief networks, were
not discussed in class, so a small introduction is provided
before discussing them in the context of the emotion prediction
problem.

A. Regression

Regression analysis is commonly used among many of the
reviewed papers. For instance, Tseng et al. utilizes multi-
output support vector regression (SVR) machines to train their
models and compare their performance with the performance
of other models trained using multi-task learning (MTL) and
single-task learning (STL) [5]. This algorithm works similarly
to the optimization of single-output SVR; multi-output SVR
learns the mean regressor \( \mathbf{w} \) for all tasks \( 1, ..., T \) and finds
small vectors \( \mathbf{v}_1, ..., \mathbf{v}_T \) that adjust the mean regressor to
account for the task relatedness while predicting the output
of each task and minimizing the overall prediction error [5].
Yu and Sano also use regression models to predict the next
day’s mood, health, and stress scores and then evaluate the
performance of the various algorithms used based on these
regression models [6]. In a previous paper, Yu et al. also
predict next day’s wellbeing but instead by developing person-
alyzed, regularized MTL regression models [7]. Additionally,
Wang et al. runs bivariate regression models before running
a prediction analysis using gradient boosted regression trees
(GBRT) [8]. The purpose of regression in this paper is to
analyze the self-reported EMA scores and their association
with the passive sensor data as well as to better understand
how practical it is to predict these scores. Lastly, Jaques et
al. utilize Gaussian process regression as the base model for
domain adaptation in an attempt to obtain a very personalized
prediction of emotion and wellbeing [9]. The popularity of
this method is a testament to its usefulness when it comes
to prediction, understanding the correlation between variables,
and assessing the performance of the model.

B. Convolution Neural Network

In recent work [10], CNN has been proposed for emotion
recognition. The input data, like other methods, is composed of
ECG signals (32 channels) and peripheral signals (temperature,
etc.). There are two models proposed in this work. The first
model only takes ECG signals as input, and the architecture is
composed of multiple 2D-CNN layers with maxpooling fol-
lowed by drop out layer, fully-connected MLPs, and a softmax
at the end. The second model takes both ECG and peripheral
data as input through multiple independent channels followed
by concatenation and MLP. All activations are ReLu, except
the last layer which is softmax. The loss function is cross-
entropy and the ADAM optimizer is used.

The output/labels are valence and arousal, but they are binned
to form 3 classes for each category. They also fuse multiple
modalities together but do not report the results because it
performs worst that a single modality model.

C. Long Short-term Memory Networks

Long short-term memory (LSTM) networks are an extension
of recurrent neural networks. They can process temporal data
that comes in sequences and are able to learn long-term
dependencies, so they are useful for prediction when working
with time-series data. Yu et al. apply this method for wellbeing
prediction [7], and then, in a later paper, Yu and Sano combine
a LSTM network with a convolutional neural network (CNN)
and compare its performance with that of a deep LSTM
network [6]. A LSTM network is a participant-independent,
generalized method that works well with temporal data and
can be employed to try to achieve a predictive model that
adapts well to new participants.

D. Reinforcement Online Learning

The work presented in [11] combines online learning with
reinforcement learning. Since these methods were not dis-
cussed in class, we first present a brief summary. As opposed
to conventional batch training with the entire training data, on-
line learning trains the model with one sample at a time either
because the data is sequential or is not available completely at
a certain time, e.g streaming data [12]. Online learning allows
the model to adapt as new data comes in, and the model is
refined over time compared to one-time batch training with
fixed computation complexity. Reinforcement Learning (RL)
defines a notion of agent that learns the optimum set of actions,
also known as policy, by interacting with its environment.
The distinguishing aspect of RL is the notion of reward that

drives the agent towards learning the optimum policy. For each action, a reward is defined, and the agent chooses the next action by maximizing the expected value of future reward. In this work, the classification problem is formulated as minimization of a loss function with L1 regularization in a stochastic gradient descent setting to find optimum weights of linear classifier. Secondly, for RL problem formulation, each sample or all data points at time step \( t \) represent the state at time \( t \). After using the data up until time \( t \) to find weights in online ML setting, the model is fitted to the next data point \( x_{t+1} \). The estimated label \( \hat{y}_{t+1} \) is compared with true label \( y_{t+1} \) to determine the reward:

\[
R = \begin{cases} 
1 & \text{if } |\hat{y}_{t+1} - y_{t+1}| < \sigma \\
0 & \text{otherwise} 
\end{cases}
\]  

When the reward is 1, the model is kept as is. However, when it is 0, implying it performed poorly, the model is updated. Thus, in that scenario, the online ML training routine is executed using \( s_{t+1} \). The linear classifiers used to evaluate the proposed method include least squares (LS) and support vector regression machine (SVR).

**E. Feature Selection: Deep Belief Networks**

The work in [13] proposes using Deep Belief Networks (DBN) for feature selection on EEG data to predict arousal, valence, and liking of a user to a one-minute video. The authors argue that hand-picked features by experts or feature selection using PCA is labor-intensive and not scalable, whereas using an automated mechanism to extract features from raw EEG data using DBN is scalable and adaptive when physiological data or the task changes. However, it is important to note that the authors do not use PCA as a baseline in their performance evaluation, and this claim about PCA scalability is not convincing since ER datasets are usually small in size because of limitations involved in collection of survey data from actual humans.

Deep Belief Networks are a semi-supervised class of deep neural networks with multiple hidden layers [14]. The layers are connected, but the hidden units in one layer are not. When fed unlabeled data, they provide feature selection, and when labels are provided, they can be used for classification. The main difference between neural networks and DBN is that DBN is composed of Restricted Boltzmann Machines (RBM) as the building blocks. An RBM consists of one visible and one hidden layer with no connections between nodes of same layer. An important property of RBMs is that the hidden units are conditionally independent given the visible states. As shown in Fig.2 the network is trained in steps, with one component at each step from bottom-up (or left-right in the figure). At step 1, Input Layer acts as visible layer and Hidden Layer 1 (H1) parameters are learned. In step 2, H1 acts as visible layer and Hidden Layer 2 (H2) parameters are learned. At step 3, H2 acts as visible layer and layer 3 is trained. For supervised classification tasks, a softmax layer is added at the end, and the weights are updated using conventional back-propagation.

The work in [13] utilizes DBN to first extract features from raw EEG, EOG, and EMG data in an unsupervised fashion. After feature selection, the model is trained using backpropagation to classify data for arousal. Separate binary classification models are trained for valence and liking of video. It must be noted that the signals are not truly raw signals because they are pre-processed using notch and band-pass filters for noise reduction. The performance and experiment details are discussed in section IV.

**F. Multi-task Learning**

Multi-task learning (MTL) is a method frequently used in a majority of the papers reviewed for this project in conjunction with the other models already mentioned. This technique allows for similarities and differences between tasks to be accounted for while, at the same time, solving multiple tasks. For the sake of space, this method is only mentioned briefly here and its applications and performance will not be discussed in depth.

**III. DATASETS**

Physiological data for emotion regulation (ER) is hard to collect for two main reasons. Firstly, the ground truth is very difficult to determine. There is no sensor that can directly measure happiness or sadness. Therefore, we have to rely on an individual’s judgment of their emotion, which leads us to the second challenge associated with this problem: it is a user-centric study. Since the experiments require actual reporting from a human subject, the data collection process is tedious and expensive. For the same reason, most (ER) datasets are relatively small and involve no more than 30-50 participants at a given time. On the other hand, the physiological signals are collected through multiple channels at high frequency and are, therefore, high-dimensional. Additionally many physiological
signals like EEG require a lab-setting. Unlike wearable data (like skin temperature), lab-setting experiments are hard to conduct and can not be scaled to large population and longer time periods. Because of all these challenges, most researchers utilize the small number of open-source datasets available online. All the papers we read for this project utilized one of the 3 datasets: DEAP, SNAPSHOT, and CrossCheck. We present a brief summary of these datasets below for two main reasons. Firstly they are used in almost all of the ER research. Instead of discussing them separately for each method/paper, we present them here to void repetition in interest of space. Secondly, they will provide the reader an insight into ER data and its characteristics based on which the reader can decide which ML methods would be most suitable to overcome the challenges in this domain. We discuss each dataset in context of 3 properties:

- Curse of dimensionality
- Heterogeneity in sources
- How is ground truth determined?

A. DEAP

This multimodal dataset was collected for 32 participants as they watched 40 one-minute long music videos. While the participants were watching the videos, EEG, face video, and physiological signals, including skin resistance, skin conductance, temperature, and EOG, were collected at high frequency. After watching the video, the participants completed an online self-assessment form rating the videos based on arousal, valence, and dominance, on a scale of 1-9 which is used as ground truth in most papers. After pre-processing and downsampling, the feature matrix X is 40x40x8064, where 8064 is the number of features, 40 is the number of channels (32 for EEG and 9 for other physiological), and 40 is the number of videos/trials. The label for each trial/video is a 4x1 vector with ratings for arousal, valence, dominance, and liking. It can be observed that \( p >> n \), and, therefore, this dataset suffers from the curse of dimensionality. Furthermore, data is multimodal and, thus, coming from heterogeneous sources. Each sensor might experience different noise. The labels take continuous values from 1-9, so this dataset can be used for both regression and classification.

B. SNAPSHOT

SNAPSHOT is also a multimodal dataset \([15]\) collected by researchers at MIT from 2013-2017 with college students as participants. The study was conducted over multiple different time periods (avg 2 months each) during each academic term for 4 years. Different students were recruited in each academic term and the distribution is shown in figure 3. Four different types of data were collected: mobile data, physiological data, survey, and weather data. For mobile data, call logs, sms logs, GPS, and screen time were recorded. From wearables, the physiological data is comprised of electrodermal activity (EDA) measured as skin conductance (SC), skin temperature (ST), and 3-axis acceleration (AC) collected at high frequency. Online surveys were filled by participants each morning and evening and contained information about drugs intake, alcohol, sleep time, naps, exercise, and academic information. For ground truth emotional state, the following EMAs were filled by each participant: State Anxiety Score, Trait Anxiety Score, Physical Component Score, and Big 5 Personality Test. Altogether, there were around 240 participants in the study. The physiological data was collected at high frequency, so it is downsampled by taking mean and variance for each day (since labels are available for each morning and evening). After pre-processing, there are around 400 features. If each academic term is used separately, then it becomes a \( p > n \) dataset that suffers from curse of dimensionality since the number of participants at any given time are small. The problem is reduced if all data from 2014 to 2017 is integrated together. Data is highly heterogeneous and many sources, such as GPS and wearables, suffer from high noise. The ground truth is collected on a scale of 1-100, so it can be used for both regression and classification.

C. CrossCheck

The CrossCheck dataset was collected from 61 participants by the CrossCheck system over the course of 6,132 days \([5]\). This system continuously and passively collected raw sensor data to record both the behavioral and environment rhythms of the participants, including data on app usage, acceleration, calls and SMS, screen on/off activity, location,
ambient environment, speech and conversation, and sleep [5] [8]. Additionally, every 2-3 days the system prompts users to report their EMA scores, which serve as ground truth. This high-dimensional dataset is heterogeneous, given the heterogeneity of both patients and schizophrenia symptoms, as well as multivariate. Due to the nature of how the data was collected, the data must be preprocessed before use. Data cleaning is an important part of this process due to some participants not being a part of the study for a long enough period of time. Additionally, there is missing data due to broken sensors or sensors not being charged, resulting in days with little data collected. Data cleaning reduces noise present as a result of any missing data. Tseng et al. also extracted rhythm features from the passive sensor data while preprocessing the data [5].

IV. EXPERIMENTAL EVALUATION

The purpose of this section is to provide a birds-eye view of experimental evaluation of all methods. Since it was not feasible for us to do the non-trivial data preprocessing and implement all these methods by ourselves, we report some interesting results for the original papers. Please note that while some papers use the same dataset, their preprocessing and experiment settings are very different, and therefore, we cannot draw a comparison between reported performances. Before moving to the results, there are some comments about experiment settings. First of all, Mean Absolute Error (MAE) is not the best metric because it only shows absolute error about which we can not conclude whether it is high or low. Compared to MAE, normalized scores are more informative (indicating whether the model predicted certain emotional states or not). Secondly, along with prediction accuracy, false positive rate and false negative rate can also provide more insights. Please also note that in most papers, hyperparameter tuning was either not conducted or not reported in the paper. The prediction accuracy for DBN and CNN is around 60% which is slightly higher than the corresponding baselines but is slight not much better than random (50%). For the remaining methods, the metric is MAE and its hard to infer whether its a large error or small. However, all of them are performing better than their baselines.

V. COMPARISON BETWEEN DIFFERENT METHODS

The comparison between different methods is provided in Fig. 5. The crux of this analysis is that the choice of model should be determined based on the characteristics of the available dataset. If the data is spatiotemporal, we should deploy LSTM, as it learns from sequences and can handle the vanishing gradient problem. Secondly, the specific goal of the experiment also plays a crucial role in the selection of model. If we are doing offline one-time experiment/evaluation to predict emotion, then regression, CNN, and LSTM (temporal data) are all reasonable choices. However, if, in addition to predicting emotion, an intervention (recommendation to regulate emotion) is also required, then an online method should be deployed. This experiment would encounter very dynamic data due to change in environment and circumstances. Therefore, online methods such as ROL and DBN, are more effective. Finally, we should consider the fact that the datasets in this domain have a small number of samples (especially labels) because collecting EMA data is expensive and time-consuming. Therefore, low complexity models should be preferred.

VI. CHALLENGES AND FUTURE WORK

A. Feature Engineering

In most papers, feature selection is not performed. Furthermore, most physiological data is collected at high resolution (order of kHz). However, since labels are not available at the same resolution, the data is downsampled by a huge scale using simple methods like taking mean or variance. This results in a huge loss of information. In the future, more advanced feature engineering methods and encoding schemes can be deployed to retain this information and improve the performance.

B. Dataset Bias

It can be observed from section III that most studies are conducted with only college students, which introduces a huge bias. In future works, more datasets from more diverse population sections should be collected to reduce this bias.

C. EMA Sampling

The frequency at which surveys are conducted in order to collect ground truth and some feature data (like SNAPSHOPT data) is critical. A higher frequency would frustrate the user, and they might give up filling out the surveys. A low frequency is detrimental for the model’s learning process. Furthermore, sometimes the user can be in a situation, like driving, when he can’t answer the survey. These are all potential issues that can be addressed in future works with solution in the direction of non-uniform and more intelligent sampling.

D. Combining adaptability with sequence prediction

The works that we saw were either utilizing spatial data only in an adaptive setting (ROL) or utilizing spatiotemporal data in sequence prediction model like LSTM. In future, the adaptive setting can be extended to integrate spatiotemporal data.

E. Scalability and Generalizability

As observed in section III, most datasets are collected in either a lab-scale setting or in a specific (college) setting. It is important to ensure that the proposed methods are generalizable to real-life settings. Furthermore, the current datasets have an extremely limited number of users. Scalability of methods to larger populations is also an issue that should be kept in mind while designing future solutions.
F. Multimodal data challenges

Since emotion is depicted by a huge number of modalities, some modalities (like the ones obtained from wearables) are collected at a much higher resolution than other. Alignment and synchronization of multiple modalities and their fusion is a key challenge.

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### Table: Multimodal Data Challenges

| Model | Model Complexity | Spatial-temporal data | Training/learning time complexity | Adaptability to new data/task changes | Curse of Dimensionality | Inference | Feature Learning/Extraction | Missing values | Vanishing gradients problem |
|-------|-------------------|-----------------------|-----------------------------------|---------------------------------------|------------------------|----------|----------------------------|---------------|-----------------------------|
| Regression (Linear) | Low model complexity (linear regression) | Can only deal with spatial data | $O(n^2p + p^3)$ | It is not an online algorithm, so it is not adaptive. | It does not suffer from Curse of dimensionality. | We can draw inference. | Helps in feature selection like Lasso. | Can not deal with it | Does not suffer from it. |
| CNN | low model complexity | Can deal with both spatial and temporal data | $O(p + n \times k)$ | It is not an online algorithm, so it is not adaptive. | Suffers from it just like a normal NN | Just like a normal NN, inference cannot be drawn because our data is not large data. | Each layer is extracting some features. High level features are extracted in bottom hidden layers and more fine details are extracted in top layers. | Can not deal with it. Need to preprocess data | Suffers from it |
| LSTM | low model complexity (O(1) where t is length of sequence) | Can deal with both spatial and temporal data | $O(n \times w \times l)$ | It is not an online algorithm, so it is not adaptive. | Suffers from it just like a normal NN | We can observe the performance of LSTM for different sequence lengths to deduce the dependency of present on the length of past. However, since there are multiple hidden layers, we can’t get direct inference. | LSTM is a neural network therefore it does extract features at each layer. | Can not deal with it. Need to preprocess data | Doesn’t suffer from it |
| ROL (in the context of LS and SVM) | LS is same as that of regression and is therefore low | Can only deal with spatial data | Training time for LS/SVM with ROL is much higher than conventional LS/SVM (the exact expression is not provided in the paper) | It is an online algorithm so it can adapt the model as new data comes in. | It does not suffer from Curse of dimensionality. | Yes, we can draw inference from LS because we can look at statistical significance | LS does Feature selection by assigning lower weights to unimportant features | It can not handle missing values | Doesn’t suffer from it |
| DBN | Low complexity because at each step looks at only 2 layers | Can deal with both spatial and temporal data | Training time is much longer than normal NN because of step-wise training (can’t do parallelization) | Online learning algorithm therefore can adapt to new data and task changes. | Can suffer depending on the architecture | Yes, we can draw inference as it is very useful method for feature extraction | Very effective for unsupervised feature extraction | Can not handle missing data | Does suffer from it |

Fig. 5. Comparison table
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