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Predicting Loneliness Using Machine Learning and Self-Logged Behavioural Data

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Abstract

Loneliness is a growing public health concern, particularly among older adults, and has been linked to adverse physical and mental health outcomes. This study presents a machine learning approach to predict levels of loneliness using behavioural and emotional data collected from 124 participants through a mobile phone application over a 71-day period. The dataset includes 27 features derived from self-logged information such as wellbeing scores, mood fluctuations, and time spent in various home locations.

Feature selection was applied to identify the most discriminative indicators, with classification and regression models evaluated using both Support Vector Machine (SVM), and Random Forest (RF). We applied feature selection to identify the most discriminative indicators and evaluated both Support Vector Machine (SVM) and Random Forest (RF) models for classification and regression. The highest classification accuracy—69.19% on a 7-point loneliness scale—was achieved using a five-fold SVM with the top 13 features. In the regression task, the best performance was observed using 26 features, resulting in a minimum Mean Squared Error (MSE) of 0.6752.

These findings indicate that a selected subset of behavioural and emotional features can offer a meaningful estimation of loneliness levels. This has potential to inform the design of real-time, personalised digital tools aimed at identifying and supporting individuals at risk of loneliness.

Keywords: Loneliness prediction; Feature selection; Behavioural data; Mood analysis.

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1. Introduction

Loneliness is a complex and pervasive negative emotional experience that arises from the discrepancy between the desired and actual quality or quantity of social relationships [1]. This feeling can manifest as a chronic state, when a person feels lonely most of the time, or as a transient experience that comes and goes. It may also occur during specific times of the day or week, such as every Sunday or during public holidays.

In 2020, approximately 1.7 million people aged 85 and over made up 2.5% of the total population in the UK. This figure is projected to nearly double by mid-2045, reaching 3.1 million and comprising 4.3% of the population [2]. According to Age UK (2018) [3], an estimated 1.9 million older adults in England often feel lonely, and this number is expected to rise to 2.1 million by 2030.

Loneliness is not just an emotional state; it has significant consequences for both mental and physical health. It is associated with increased risks of morbidity, including heart conditions, and even premature death. Mental health is deeply intertwined with physical health and is influenced by broader developmental factors such as poverty, employment, economic growth, and social justice [4]. Research has shown that weak social connections can increase the risk of coronary heart disease by 29% and stroke by 32% [5]. Loneliness may also impair brain function and weaken the immune system, contributing to various additional health problems. Previous studies have demonstrated an association between loneliness and low mood [6].

Early detection of loneliness is crucial, as it enables timely intervention through counselling, social support, or community engagement, helping individuals build meaningful connections and improve overall wellbeing. Healthcare professionals play a vital role in recognising and addressing loneliness, ultimately enhancing patients' quality of life and health outcomes. By diagnosing loneliness, we take a critical step towards improving both mental and physical health and strengthening social functioning [7].

It is important to note that loneliness is a multidimensional construct, and no single measurement method captures its full complexity. Researchers often employ a combination of tools to assess loneliness, most commonly using self-report questionnaires or surveys. Two widely used scales are the UCLA Loneliness Scale [8] and the De Jong Gierveld Loneliness Scale [9,10], which ask individuals to evaluate their feelings of loneliness using Likert-type rating systems.

In recent decades, technology has significantly transformed daily life. Smartphones have become essential tools, not only for communication but also for supporting daily routines through various applications. Importantly, smartphones can also be used to collect behavioural data that may correlate with loneliness. Detecting loneliness and predicting fluctuations in loneliness levels could enable digital platforms, and their human users to recognise meaningful trends, identify risk factors and correlates of loneliness, allocate resources where they are most needed. Recent advances in machine learning, such as classifying naturally collected behavioural data, have enabled new technical approaches to detecting loneliness [11].

1.1. Background and Literature Review

In the healthcare domain, machine learning (ML) has been widely adopted to develop predictive models that support clinical decision-making [12]. Various ML models have been designed to monitor and detect health-related issues in older adults, including changes in activity patterns [13].

Beyond physical health, machine learning has also demonstrated potential in addressing mental health concerns. Predictive models have been applied to detect conditions such as bipolar disorder [14], delirium in the elderly [15], emotional wellbeing [16], and social emotions [17]. Increasing attention has also been given to the application of ML for recognising loneliness and social isolation.

Site et al. (2022) [18] demonstrated the effectiveness of using real-time indoor and outdoor mobility data from older adults to predict loneliness levels with high accuracy. The study collected mobility features such as distance travelled, estimated speed, and frequently visited locations, achieving classification accuracies between 90% and 98%, with XGBoost outperforming other models. However, the loneliness was categorised into only three discrete levels.

Lin et al. (2024) [19] developed a machine learning model using data from the Chinese Longitudinal Healthy Longevity Survey (CLHLS). The model identified marital status, social interactions, functional limitations, and subjective health measures as key predictors of loneliness. A multi-layer perceptron (MLP) model showed strong performance in loneliness risk prediction in binary classification problem.

Similarly, Bello-Valle et al. (2022) [20] confirmed that loneliness and social isolation in older adults could be predicted using features derived from behavioural patterns, demographics, and communication habits. Their study involved 100 older adults and achieved an accuracy of 70% in detecting loneliness and 80% for social isolation. Predictive attributes included gender, age, marital status, and a wide range of call and message patterns, such as average call time and room occupancy metrics.

Pulekar and Agu (2016) [21] introduced Socialoscope, a smartphone-based system designed to detect loneliness passively by monitoring calls, SMS, browsing activity, and social media use. While the system achieved a classification accuracy of up to 98% across three levels of loneliness, the small sample size (nine international students over two weeks) limits the generalisability of the findings.

Li et al. (2016) [22] also explored loneliness detection using mobile phone data. In a study involving 46 participants assessed via the UCLA Loneliness Scale, participants were grouped into "risk" and "non-risk" categories. Features such as app usage, communication logs, Bluetooth proximity, GPS, and activity data were analysed. The Random Forest classifier achieved the highest accuracy at 70.68%, although the study did not aim to predict specific levels of loneliness.

Sarhaddi et al. (2022) [23] employed passive sensing using smartwatches to detect maternal social loneliness during late pregnancy and the postpartum period. The study, which included 31 participants, extracted physiological features such as resting heart rate (HR), heart rate variability (HRV), sleep metrics, and physical activity. Machine learning models including decision trees and gradient boosting achieved high F1 scores of 0.897 and 0.871, though they also focused on binary classification rather than level prediction.

Rahayu et al. (2022) [24] examined loneliness detection through speech and transcribed text using deep learning models. Combining Deep Neural Networks (DNNs) and Long Short-Term Memory (LSTM) architectures, the study reached 100% accuracy on textual data and 99.61% on speech. However, like several others, the study focused only on binary classification rather than detecting varying levels of loneliness.

Lastly, Doryab et al. (2019) [25] conducted a 16-week longitudinal study involving 160 college students, collecting behavioural data from smartphones and wearable devices (Fitbits). By applying statistical analysis, data mining, and machine learning models (gradient boosting and logistic regression), the study achieved 80.2% accuracy in recognising binary levels of loneliness and social isolation.

1.2. Contribution

Most previous studies on loneliness recognition have focused on binary classification, typically distinguishing only between "lonely" and "not lonely" individuals. While binary detection of loneliness is useful for initial screenings, predicting the level of loneliness provides a more comprehensive understanding, enabling early intervention, personalized care, and effective monitoring. This approach is essential for addressing the complex nature of loneliness and its impact on mental health [26].

Additionally, most earlier studies relied on very small datasets collected from a limited number of participants, which significantly constrains the generalisability of their findings. Moreover, none of the prior work has incorporated mood-related attributes into their data collection, leaving out potentially critical indicators.

In contrast, the current study collects temporal behavioural, and mood using a custom-developed mobile application. From this dataset, we extracted a comprehensive set of features that capture temporal changes in mood, enabling a more nuanced investigation into the relationship between mood dynamics and loneliness. Some of these features are novel and have not been applied to this domain in previous research.

To evaluate the relevance of these features for classification, we developed a feature selection framework that employs the Joint Mutual Information Maximization (JMIM) method [27], a state-of-the-art technique known for its effectiveness and computational efficiency. Furthermore, this study goes beyond binary classification and explores the prediction of loneliness across seven levels of intensity, offering a more detailed and realistic representation of the loneliness spectrum.

The remainder of the paper is structured as follows: Section 2 describes the data collection process; Section 3 outlines the experimental setup; Section 4 presents the results; and Section 5 discusses the findings and concludes the paper.

2. Dataset Collection

The dataset used in this study were collected through The Circle app [6], which is a custom-designed mobile phone application developed as part of the SERVICE project, which sought to raise older adults' awareness of their social relationships. Fig 1 shows screening shots of the app. The app enabled participants to self-log various aspects of their daily experiences, with a particular focus on mood and loneliness. Through the app, participants were asked to self-log the information that is shown in the table 1. The design process of this app, including the qualitative analysis, is explained in [6].

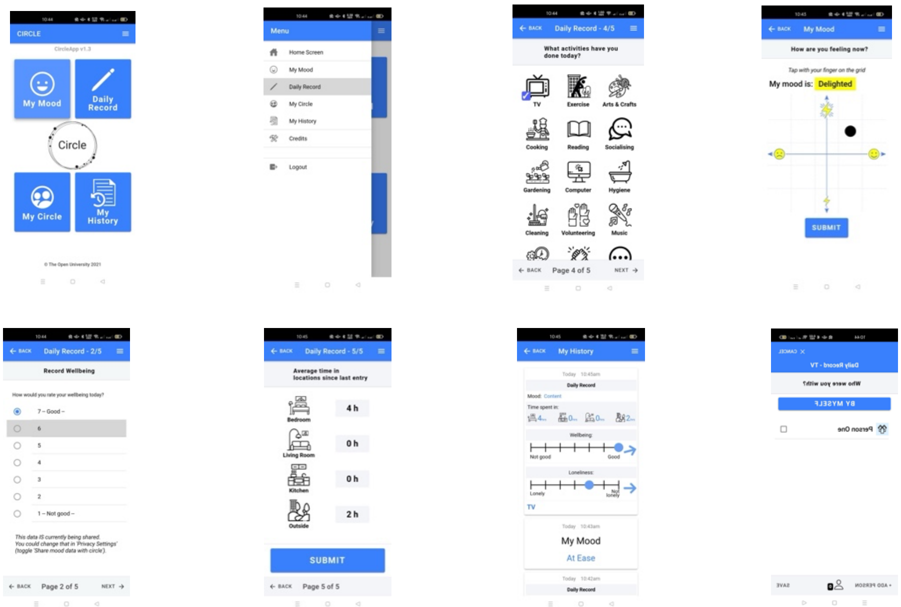

Fig. 1. Screen shots of Circle app

Table 1. List of raw features that are collected through the app.

Raw feature	Data type
Mood	Categorical
Mood Positivity/Negativity	discreet
Mood Activity/Passivity	discreet
Wellbeing	discreet
Pastimes Activities	text
Spoken to anyone?	binary
Hours in bed	discreet
Hours on sofa	discreet
Hours in kitchen	discreet
Hours in garden	discreet

Participants could select one of eight mood options: Excited, Happy, Relaxed, Calm, Bored, Sad, Annoyed, or Nervous. Treating this data as purely categorical introduces a key limitation as it ignores the inherent relationships between different emotional states. For example, if a participant selects Happy instead of Relaxed, these emotions are more closely related than, for instance, Relaxed and Sad. However, this nuance is lost when emotions are treated as unrelated categories. An alternative approach is to represent emotions along two ordinal dimensions, Affect and Valence, each ranging from -2 to +2 [28]. This framework captures both the intensity and quality of emotional states. In this study, these dimensions are captured using the variables Mood Activity/Passivity and Mood Positivity/Negativity, respectively.

A total of 124 participants were recruited, 37 male, and 87 female, average age is 67, average deviation is 9. the participant used the app to self-log the information mentioned above between05/01/2022 and 16/03/2022. A total time stamped 2992 observations were recorded, representing a sequence of logged actions. To ensure data quality, only participants whose loneliness records exhibited variation in levels were included in the analysis.

3. Experimental Work

This study aimed to predict self-reported loneliness levels, measured on a 7-point Likert scale (1 = not lonely, 7 = extremely lonely), using temporal behavioral, mood, and interaction data collected through a custom-built mobile application. The app was developed as part of the SERVICE project and allowed participants to self-log various indicators related to mood, activity, and wellbeing. The dataset consists of time series data with 10 raw features, collected from 124 participants, resulting in 2,992 recorded instances. Figure 2 shows the pipeline used in this study which consists of 4 stages starts with data preprocessing, feature significance analysis, models (classification/ regression), and models testing.

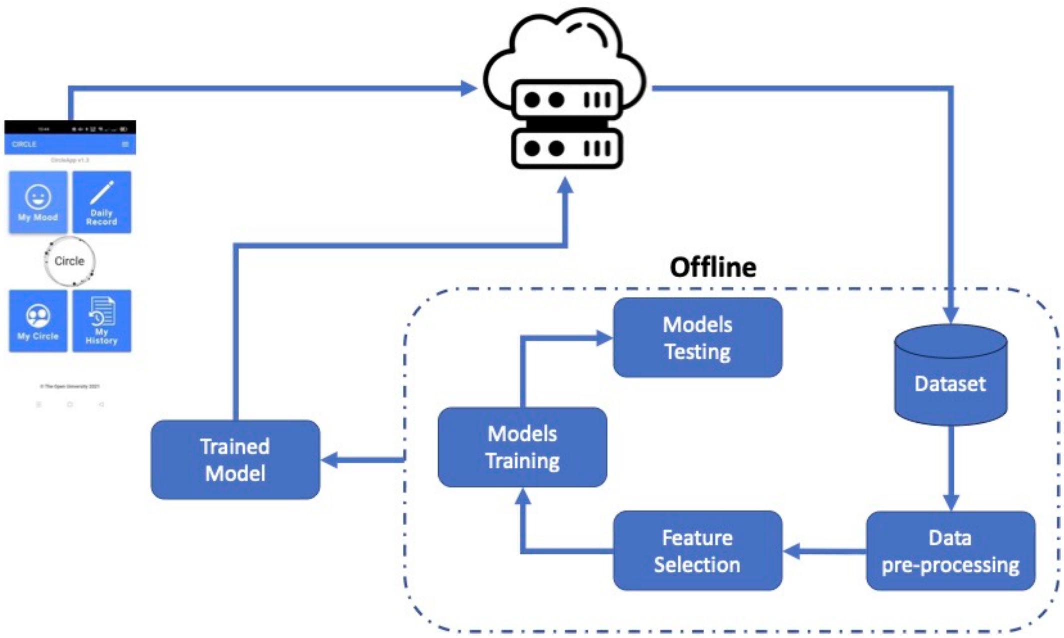

Fig. 2. The proposed automatic loneliness level detection

3.1. Preprocessing and Feature Engineering

Loneliness is understood as a cumulative experience, shaped and influenced by an individual's past activities, interactions, emotions, and events over time [11, 29]. To explore this dynamic, the dataset was segmented into intervals based on changes in self-reported loneliness levels. All logged activities, mood entries, and wellbeing data recorded between two consecutive loneliness assessments were treated as potential factors influencing the subsequent loneliness score. The Pastimes Activities feature was also analysed to quantify the number and type of activities undertaken during each interval. The “Spoken to anyone?” feature was excluded from the dataset, as this raw variable appeared empty in the majority of observations.

Beyond the raw features collected, the next phase involved feature engineering, where a new set of features was derived. Among the original variables, Mood Positivity/Negativity, Mood Activity/Passivity, and Mood exhibited the greatest variation between successive loneliness readings, suggesting that they carry more informative value than the rest of the feature set. Statistical analyses were conducted on these variables individually to identify meaningful patterns. This process resulted in the extraction of 11 new features, listed as entries 9–19 in Table 2.

Furthermore, seven additional features were derived by conceptualising Mood Positivity/Negativity and Mood Activity/Passivity as coordinates in a two-dimensional space. Each pair of readings from these variables was treated as a point in this coordinate system. The Euclidean distance and the direction of change (i.e., the sign) between each pair of consecutive points were computed. Based on these calculations, the following features were extracted: maximum distance, minimum distance, average distance, standard deviation of distances, and the number of times the directional change between consecutive points was positive or negative.

3.2. Feature Significant analysis

Feature selection is employed in this study as a dimensionality reduction strategy for two key reasons. First, it enables the evaluation of feature significance in relation to the classification task. Second, it enhances the performance of the learning algorithm by eliminating redundant and irrelevant features that could negatively impact model accuracy and generalisation.

Table 2. Total set of features.

No	Feature	Description
1	Wellbeing	Self-reported wellbeing level, measured on a 7-point Likert scale (1 = not well, 7 = extremely well).
2	Activities Count	The total number of activities performed prior to the loneliness assessment.
3	Last Mood Positivity/Negativity	The last mood Positivity/Negativity entry recorded before the corresponding loneliness recorded.
4	Last Mood Activity/Passivity	The last mood Activity/Passivity entry recorded before the corresponding loneliness recorded.
5	Hours in bed	Cumulative time spent in bed before the loneliness level was recorded.
6	Hours on sofa	Cumulative time spent on the sofa before the loneliness level was recorded.
7	Hours in kitchen	Cumulative time spent in the kitchen before the loneliness level was recorded.
8	Hours in garden	Cumulative time spent in the garden before the loneliness level was recorded.
9	Last Mood recorded	The last mood entry recorded before the corresponding loneliness recorded.
10	Mood Change Count	The number of times mood changed before the loneliness level was recorded.
11	Mood Positivity – Minimum	The lowest value of mood positivity recorded prior to the loneliness assessment.
12	Mood Positivity – Maximum	The highest value of mood positivity recorded prior to the loneliness assessment.
13	Mood Positivity – Range	The difference between the maximum and minimum recorded values of mood positivity.
14	Mood Positivity – Maximum Change	The largest change between two consecutive mood positivity readings.
15	Mood Positivity – Difference	The difference between the first and last mood positivity values recorded between two loneliness assessments.
16	Mood Activity – Minimum	The lowest value of mood activity recorded prior to the loneliness assessment.
17	Mood Activity – Maximum	The highest value of mood activity recorded prior to the loneliness assessment.
18	Mood Activity – Range	The difference between the maximum and minimum recorded values of mood activity.
19	Mood Activity – Maximum Change	The largest change between two consecutive mood activity readings.
20	Mood Activity – Difference	The difference between the first and last mood activity values recorded between two loneliness assessments.
21	Mean Distance	The average Euclidean distance between consecutive mood points (in ordinal emotion space) between each pair of loneliness recordings.
22	Maximum Distance	The largest Euclidean distance between two consecutive mood points during the interval.
23	Minimum Distance	The smallest Euclidean distance between two consecutive mood points during the interval.
24	Number of Positive Directions	The number of times the directional change between consecutive mood points was positive.
25	Number of Negative Directions	The number of times the directional change between consecutive mood points was negative.
26	Distance Standard Deviation	The standard deviation of Euclidean distances between all consecutive mood points.

To this end, the study adopts the Joint Mutual Information Maximization (JMIM) method to identify a subset of features most relevant for the classification task. JMIM was chosen based on its demonstrated effectiveness in outperforming several state-of-the-art filter methods, as well as its computational efficiency.

The JMIM algorithm is based on mutual information and utilises a 'maximum of the minimum' selection criterion. It begins by identifying the single most informative feature and then proceeds iteratively, selecting one feature at a time that maximises the objective function relative to the already selected features.

3.3. Loneliness Prediction

The primary objective of this study was to predict levels of loneliness using machine learning techniques. To achieve this, two well-established classification algorithms were employed: Support Vector Machine (SVM) with a RBF kernel, and Random Forest (RF). These classifiers were chosen for their robustness and their ability to perform effectively with minimal assumptions about the underlying data distribution.

All experiments were conducted using the MATLAB Statistics and Machine Learning Toolbox. A five-fold cross-validation strategy was adopted to evaluate the significance of the input features. In each fold, 20% of the dataset was reserved for validation, while the remaining 80% was used for training. This procedure was repeated five times, ensuring that every subset of the data was used once as the validation set.

To assess the discriminative power of individual features, an incremental evaluation approach was applied. Beginning with the most significant feature, additional features were added one at a time to the feature subset. After each addition, classification accuracy was measured to evaluate the effectiveness of the updated subset. It is important to note that the reported accuracy at each step reflects the performance of the full selected subset, not just the newly added feature.

In parallel with the classification task, a regression approach was also implemented to predict loneliness levels as a continuous outcome. The same dataset was used, with the only difference being the treatment of the target variable. SVM regression, and RF regression models were applied using the same five-fold cross-validation framework to ensure consistency and comparability across classification and regression tasks.

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4. Results

This section describes the results of applying the proposed framework to define the significant features, and predict the loneliness level using the collected features.

4.1. Feature Selection

The feature selection process resulted in a ranked list of 27 features which is shown in table 3. This analysis provides insights into which behavioural and emotional indicators are most influential in predicting perceived loneliness.

At the top of the list, *Wellbeing* emerged as the most discriminative feature. This is expected, given that self-reported wellbeing levels are directly associated with emotional and psychological states, including loneliness. Participants who reported lower wellbeing scores tended to also report higher loneliness levels, confirming the predictive power of this variable [30].

The second most informative feature was *Hours on Sofa*, followed by *Last Mood Recorded*, and *Hours in Bed*. These features reflect passive or sedentary behaviours and suggest a link between reduced activity levels and increased loneliness. In particular, the amount of time spent on the sofa or in bed may indicate social withdrawal or lack of engagement, both of which are common behavioural patterns associated with loneliness.

Activities Count ranked fifth, indicating that the frequency of engaging in daily activities is an important predictor. A higher activity count likely reflects more structured or socially engaging routines, which may buffer against loneliness. The sixth-ranked feature, *Mood Activity – Difference*, captures the change in emotional activation between two points in time, suggesting that dynamic fluctuations in energy or engagement levels also play a role in shaping loneliness perception.

Features such as *Hours in the Garden*, *Mood Positivity – Difference*, and *Mood Positivity – Maximum Change* also ranked within the top ten. These variables emphasize the importance of environmental engagement and emotional variability in understanding loneliness.

The middle-ranked features, including *Mood Activity – Range*, *Mood Change Count*, and *Maximum Distance*, reflect more nuanced aspects of emotional regulation and mood dynamics. These features highlight the cumulative effect of mood fluctuations on loneliness, reinforcing the view of loneliness as a temporally influenced experience.

In the lower half of the ranking, features such as *Mood Activity – Minimum*, *Mood Positivity – Range*, and various directional and distance-based features contribute less to the predictive power when considered independently but may still provide value when used in combination with other variables. Notably, *Distance Standard Deviation* and *Direction Trend*, which are derived from mood trajectories in emotional space, were ranked among the least informative, suggesting that the fine-grained structural properties of mood sequences may have limited standalone predictive power in this context.

Table 3. Ranked features based on their significance.

No	Feature
1	Wellbeing
2	Hours on sofa
3	Last Mood recorded
4	Hours in bed
5	Activities Count
6	Mood Activity – Difference
7	Hours in garden
8	Mood Positivity – Difference
9	Mood Positivity – Maximum Change
10	Mood Activity – Range
11	Hours in kitchen
12	Mood Change Count
13	Maximum Distance
14	Mood Activity – Maximum Change
15	Number of Positive Directions
16	Mood Activity – Minimum
17	Mood Positivity – Range
18	Maximum Distance
19	Mean Distance
20	Mood Activity – Maximum
21	Number of Negative Directions
22	Last Mood Activity/Passivity
23	Mood Positivity – Minimum
24	Mood Positivity – Maximum
25	Last Mood Positivity/Negativity
26	Distance Standard Deviation
27	Direction Trend

Interestingly, both *Last Mood Activity/Passivity* and *Last Mood Positivity/Negativity*, which reflect the final emotional state before loneliness was recorded, appeared in the lower portion of the ranking. This indicates that a broader temporal context and pattern of emotional and behavioural indicators may be more informative than isolated mood states.

Overall, the results emphasize the significance of wellbeing, sedentary behaviour, and temporal mood changes in predicting loneliness.

4.2. Loneliness Prediction

This section presents only the results from the SVM model, as it outperformed the Random Forest (RF) model. The results are illustrated in Figure 3 (a) and Figure 3 (b), showing classification accuracy and regression error (MSE), respectively, across an increasing number of selected features. As previously described, each algorithm was trained and tested incrementally, with features added one at a time according to their ranked discriminative power. For every iteration, a five-fold cross-validation approach was applied to ensure reliable evaluation and to mitigate overfitting.

In the classification task, the highest accuracy was achieved using the top 13 features, reaching 69.19%. Notably, a nearly comparable performance of 69.05% was already observed with just the top 9 features, indicating that most of the predictive power is concentrated within a relatively small subset. Performance began to decline slightly as less informative features were added, dropping to 67.59% when all 27 features were used.

For the regression task, the lowest Mean Squared Error (MSE) was recorded when using the top 26 features, yielding an MSE of 0.6752. This suggests that regression benefits from a broader feature set, capturing more subtle variations in behavioural and emotional indicators related to loneliness. The performance showed a general trend of improvement as more features were added, with some fluctuations, and a slight increase in error after the 26th feature.

An ANOVA test confirmed that the results from both classification and regression were statistically significant, indicating that the observed effects are highly unlikely to have occurred by random chance (P-values of = 4.8E-18 and 2.1E-5. respectively).

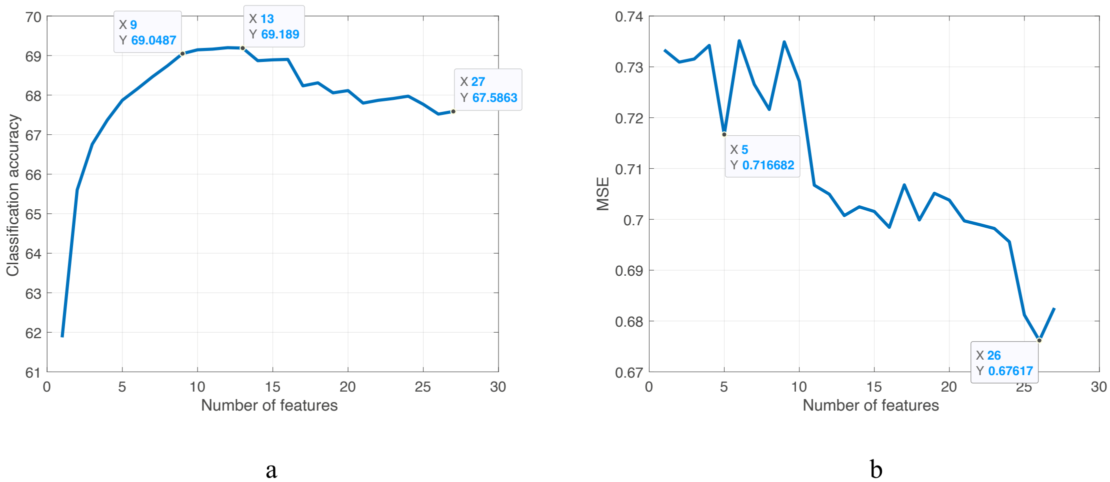

Fig. 3. The performance of the SVM algorithm: (a) Classification; (b) Regression.

5. Conclusion

This study presented a data-driven approach to predicting levels of loneliness using self-logged behavioural and mood-related data collected through a mobile application. By applying feature selection techniques and evaluating the discriminative power of individual features, we identified key indicators that contribute most significantly to loneliness prediction.

The results demonstrated that a small subset of features, particularly self-reported wellbeing, time spent on the sofa, and recent mood patterns, provided strong predictive power. Using SVM and RF classifiers, we evaluated both classification and regression models. SVM consistently outperformed RF across both tasks, achieving a peak classification accuracy of 69.19% with the top 13 features and the lowest regression error (MSE = 0.6752) with 26 features.

The study highlights the importance of considering both emotional and behavioural factors when modelling loneliness. It also shows that a well-structured feature selection process can enhance model performance while maintaining interpretability.

Future work may explore the generalizability of these findings across different populations, the inclusion of contextual or temporal variables (e.g., time of day or season), and the use of more advanced deep learning architectures to model complex emotional trajectories over time and to improve the performance. Moreover, integrating these predictive models into real-time interventions could provide meaningful support to individuals experiencing or at risk of loneliness.

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