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Original Article

Optimized Convolutional Neural Network for Accurate Personality Trait Prediction from Spending Data

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Abstract - *Understanding the link between a person's spending data and their personality traits can significantly improve applications in psychology, financial advising, and targeted marketing. This study presents an optimized Convolutional Neural Network (CNN) model to predict big five personality traits: Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism (OCEAN), and also materialism and self-control based on debit transaction data. Three main aspects of spending behavior are analyzed: overall spending behavior, category-related spending behavior, and customer category profiles. The study addresses two main research questions: (1) Can spending patterns from transaction data reliably indicate a person's psychological traits? (2) How does an optimized CNN model compare to traditional machine learning models in predicting personality? The proposed model uses Pearson correlation for feature selection and extraction, then applies deep learning for behavioral inference. Experimental results show that the CNN model achieves a classification accuracy of 99.72%, surpassing conventional methods. These findings confirm that spending data can effectively represent personality profiling, providing data-driven insights into consumer psychology.*

Keywords - *Convolutional Neural Network, Deep Learning, Personality Trait, Psychological Profiles, Spending Data.*

1. Introduction

Psychologists have long been interested in understanding human personality and exploring ways to predict it accurately. One of the most widely used frameworks for describing personality is the Big Five Personality Model, which categorizes individuals into five core traits: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (OCEAN). Traditionally, these traits have been assessed using self-report questionnaires [1]. Although widely accepted, such methods depend heavily on individuals' self-perceptions and are therefore subjective. In addition, responses may be influenced by biases such as social desirability, where individuals tend to present themselves in a more favourable or socially acceptable manner rather than providing completely honest answers.

With the rapid expansion of digital technologies, new opportunities have emerged for understanding human behaviour through objective, behaviour-based data. Digital footprints generated through everyday activities offer continuous and unbiased insights into individual preferences and habits. Among these data sources, consumer spending behaviour, particularly information obtained from debit and credit card transactions, has gained increasing attention. Financial transactions capture real-life decisions and reveal what individuals prioritize, value, and choose in their daily lives. Consequently, spending behaviour provides a practical and reliable alternative for inferring psychological traits without relying solely on self-reported information [2].

Personality traits strongly influence how individuals manage and spend their financial resources. For instance, individuals high in openness are often willing to spend on new experiences such as travel, cultural events, or entertainment. Conscientious individuals typically display careful financial planning, preferring savings and controlled spending over impulsive purchases. Extraverted individuals are more likely to allocate money toward social activities and leisure, while neuroticism may be reflected in emotionally driven or impulsive buying behaviour. Beyond the Big Five traits, materialism and self-control also play important roles in shaping spending patterns, influencing tendencies toward luxury consumption, financial restraint, or long-term saving behaviour [3, 4].

Previous studies have demonstrated meaningful links between spending behaviour and psychological profiling. However, much of the existing work relies on traditional machine learning approaches such as Decision Trees, Random Forests, and Logistic Regression. While these methods provide valuable insights, they often struggle to capture complex, nonlinear relationships present in high-dimensional transaction data. Moreover, limited research has focused on the use of optimized deep learning models capable of learning hierarchical behavioural patterns while maintaining interpretability.

To overcome these limitations, this study introduces an optimized One-Dimensional Convolutional Neural Network (1D-CNN) for predicting personality traits from spending behaviour. The proposed approach combines feature-level correlations derived from spending categories with CNN-based representation learning, enabling the model to identify subtle and meaningful behavioural patterns. This integration improves both predictive accuracy and interpretability. Experimental results demonstrate that the proposed model significantly outperforms conventional machine learning techniques, highlighting its effectiveness in uncovering psychological traits from real-world financial transaction data.

2. Related Works

Ramon et.al conducted research that employed Explainable AI (XAI) methods to predict Big Five personality traits from financial transaction data. Their study highlights the importance of making AI models more transparent by showing how global rule extraction can clearly reveal the spending patterns that are most strongly linked to an individual's personality. The results show that XAI can be used as a tool for raising the accountability level of AI-driven psychological profiling [5].

Ketipoy et.al investigated the usage of machine-learning strategies for the behaviour prediction of users within E-commerce platforms. This research opened the door between the key personality traits and customers' internet purchasing habits. The researchers implemented Machine Learning (ML) models: Decision Trees and Random Forest for forecasting the user preferences based on personality traits. The findings show a strong connection between individual personality traits and online shopping behaviour. This suggests that tailoring user interfaces to match these traits can significantly improve the overall user experience [6].

Kumar et.al. suggested a unique method for applying Machine Learning Algorithms to forecast customer purchasing patterns for premium fashion items. This study forecasts consumer purchase patterns for high-end fashion items using Machine Learning Algorithms. He studied and created models to assess spending behaviour and forecast purchasing decisions, taking into account variables such as brand loyalty and spending habits. The findings demonstrate the efficacy in the field of ML analysis and forecasting consumer behaviour in the premium goods industry [7].

Tovanich et.al proposed that this study examined transaction data from 1,306 bank customers to see if individual psychological characteristics could be determined by bank transaction data. The researchers created a complete feature set that included overall spending behaviour, temporal spending activity, category-specific spending behaviour, consumer category profiles, and socio-demographic data.

They discovered that traits such as Materialism and Self-Control are predicted with considerable precision; however, predictions for the Big Five traits were less accurate, with only Extraversion and Neuroticism achieving decent classification performances [8].

Arshad et al. presented personality prediction using several textual datasets and deep learning algorithms. This study uses the five-factor model to define personality traits in human behaviour. This study, which has been transformed by developments in computer models, uses Natural Language Processing (NLP) to predict human personality traits based on a diverse set of textual data, including essays and social media posts. The study suggests detecting the pattern and context using deep word embedding analysis models such as BERT and its different variants. Various pre-processing methods and embedding types have been employed, along with considerable hyperparameter experimentation [9].

Previous studies have explored personality prediction from social media, text, and transaction data using traditional machine learning models [6–9]. However, these methods frequently do not reflect the sequential and financial transaction's high-dimensional nature, thus resulting in limited predictive accuracy.

On top of that, the majority of research works have only dealt with the identification of changes in (e.g., consumption of e-commerce or luxury products) behaviour, to the neglect of financial profile analysis. This research solves these problems by deploying an optimized 1D-CNN model that can perform complex behavioural representations from the spending data without any supervision.

The association of spending behaviour with personality characteristics is one of the main pillars of the Big Five Personality Model, according to which traits such as conscientiousness, extraversion, and neuroticism affect the financial decisions made. By integrating these theoretically backed insights into Deep Learning Models, thus making the models more accurate and interpretable, a more appropriate and explicable link between behavioural data and human psychology is established.

3. Methodology

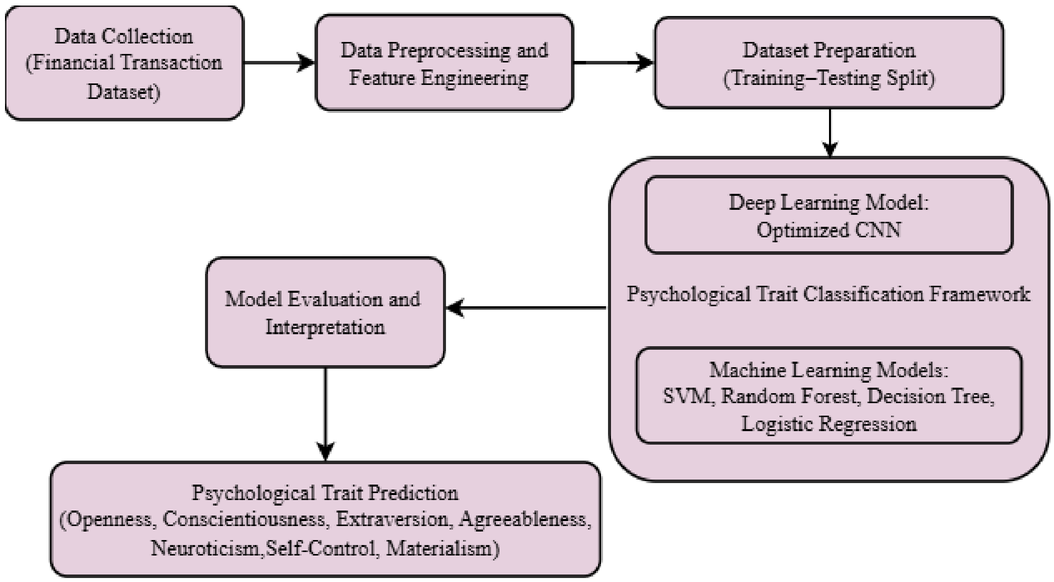

Fig. 1 Architecture diagram of the proposed method

3.1. Data

This research highlights a relationship between personality traits and a person's consumer habits. The Big Five model (OCEAN), along with Self-control and materialism personality traits, is considered in this paper. The data that is being analysed was taken from Kaggle, and it provides the individual expenditure recorded for more than 1200 clients during a period of 3 months.

The dataset includes attributes such as the customer's Unique ID (User ID), First and Last Names, Gender, Year of Birth (YOB), location of the house, country of residence, Unique Bank Identifier Number (Account Number), purchase category, transaction date, and time of transaction.

The data collected reveals a different demographic range of users from various age groups, genders, and locations, which, in turn, ensures an equitable representation of Spending Behaviour. The restriction of data to ten debit transactions per month for users is one of the criteria for data reliability and consistency; thus, only these users were taken into account in the analysis, and inactive or sparse records have been filtered out. Names and account numbers were among the personal information that was removed during the pre-processing stage.

All the data were anonymized before they were used, and personally identifiable information such as names and account numbers was removed during pre-processing. As the dataset is publicly accessible and fully anonymized, no additional permission from the participants was necessary. The study is conducted according to ethical research principles and is in agreement with the policies on the use of open data.

3.2. The Correlation between Personality Qualities and Spending Data

- Openness to Experience: People with high levels of openness typically spend more money on literature, travel, and cultural events. Their interactions, which emphasize new experiences and intellectual stimulation, demonstrate a curiosity-driven attitude.
- Conscientiousness: Highly conscientious People spend their money in a planned and organized manner. They minimize rash purchases while prioritizing long-term investments, insurance, and savings.
- Extraversion: Extroverts usually spend money on social and recreational activities. Their transactions frequently entail social gatherings, entertainment, and eating out, suggesting an extroverted and adventure-driven lifestyle.
- Agreeableness: Agreeable people spend their money on prosaically endeavours like donations, presents, and charity. They frequently refrain from lavish self-indulgence and have thoughtful financial habits.
- Neuroticism: People with high neuroticism frequently display erratic and emotionally motivated spending habits. Frequent impulsive purchases, stress-related retail therapy, and mood-enhancing events are some of the possible reasons behind their purchases.
- Materialism: Those who are materialistic place a higher value on branded things, luxury items, and unnecessary purchases. Their thirst for material belongings and social status is reflected in their spending.
- Self-Control: Budgeting, disciplined spending, and a decrease in impulsive financial behaviour are all linked to high self-control. People who lack self-control frequently indulge in unforeseen expenses and have erratic spending patterns.

3.3. Data Pre-Processing and Feature Engineering

The two types of recorded activity in the dataset under consideration are Credit Transactions (Income) and Debit Transactions (Outgoing). The balance amount decreases with a debit transaction (such as a payment, withdrawal, or purchase activity). It increases with a credit transaction (such as a salary, deposit from another party, or other revenue). To examine their behaviour, only debit transactions that accurately represent each individual's spending are retained. The next stage is to keep only those individuals with ten or more transactions each month in order to ensure a fair quantity of data per spending participation and to keep only those persons' information in the dataset who were actively making purchases. The purchase categories with at least one transaction are kept in the dataset to help lower the sparseness of the category space. Out of the remaining purchase categories, the category grouping is formed. The 15 purchase category groups formed are groceries, clothes, books, food, gambling, household spending, transportation, mobile, holiday, personal care, children, charities, health care, entertainment, and insurance. A complete feature set is created based on three factors: Overall spending behaviour (Number And Amount Of Transactions), Category-related spending behaviour (Diversity, Persistence, And Turnover), and an individual's category profile. We investigate the relationship between these features and individual psychological characteristics, examine feature families' performance, and determine the severity of psychological inference from spending records. The features considered under each type are described in Table 1.

Table 1. Description of overall, category related

Type	Feature	Description
Overall	Ntot	Total number of transactions.
	Atot	Total amount spent across all the transactions
	Aavg	Average spending per transaction.
	cv	Coefficient of variation, representing relative spending variability.
Category related	Nc	Number of distinct spending categories
	D_{cat}	Measure of diversity across different categories.
	$C_{repeat.}$	Frequency of repeated purchases within the same category
	$C_{topturn(3)}$	Turnover of the top 3 most frequently used categories.
	$C_{topturn(5)}$	Turnover of the top 5 most frequently used categories
	$C_{topturn(all)}$	Overall turnover across all spending categories.
Category Profile	C_k	Number of transactions made within category k.

The selected features are grounded in behavioural finance and psychological theory, reflecting meaningful links between spending behaviour and personality traits. The Total Number Of Transactions (N_{tot}) and Average Amount Per Transaction (A_{avg}) indicate financial activity intensity. Individuals high in extraversion and openness tend to make frequent and varied purchases, consistent with their social and exploratory tendencies [8, 13]. Category Diversity (D_{cat}) and Repeated Purchase Frequency (C_{repea}t) capture regularity and planning in expenditure, traits associated with conscientiousness and self-control. Stable and structured purchase habits often signal organized financial behaviour [3, 10].

Turnover Ratios (C_{toptum}) represent preference stability or novelty-seeking behaviour. Frequent category changes are linked with openness and neuroticism, while low turnover reflects consistent spending patterns [5]. Category Profile Features (C_k), such as luxury or charitable spending, correspond to materialism and agreeableness, respectively, highlighting the motivational aspects of financial choices [8, 12]. Pearson correlation was used to quantify relationships between these features and personality traits, ensuring that only psychologically and statistically relevant variables were retained for modelling. To analyse the data, different features generated from spending behaviour are used to determine each customer's unique psychological characteristics. Specifically, the association between the behavioural features and each person's unique psychological traits is obtained by using Pearson correlation. The correlation of overall and category-related features vs. Personality traits and the correlation of customer profile vs. personality traits are described in sections 4.1 and 4.2, respectively. Pearson's correlation coefficient r evaluates the degree of linear association between the variables x and y

$$\boldsymbol{r} = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2 \sum(y_i-\bar{y})^2}} \quad (1)$$

Equation (1) Defines Pearson's Correlation Coefficient.

3.4. Modelling

In this work, the particular focus is on developing a personality prediction model based on spending behaviour by applying machine learning algorithms. To see whether the model developed in this study worked as intended, a number of benchmark models were used in the analyses; these models were referenced in the literature review and are popular for other classification projects, so they set the standard for confirming how well the approach in question would utilize a machine learning model. These models will be described in this section [10-15].

3.4.1. Support Vector Machine (SVM)

It has proven to be efficient in both classification and regression tasks as far as supervised learning algorithms are concerned. As introduced by Vapnik, SVM works by constructing an optimal hyperplane that differentiates differently labelled samples. The method is especially useful in behavioural and personality analysis, as it can maximize its performance while dealing with large amounts of information, even dealing with cases of overfitting. Kernel Linear, Polynomial, and Radial Basis Functions (RBF) are sufficient for SVM to adapt to non-linear multi-dimensional problems.

3.4.2. Random Forest (RF)

It is better known as an ensemble learning technique for deriving multiple DT and amalgamating their predictions for good accuracy, as well as to reduce overfitting. Every tree is built on a different sample subset, and the eventual selection of the tree is achieved by the 'vote' method (classification) or averaging out (regression). Large data sets associated with spending activity can be analyzed more effectively using Random Forest, and it also captures their relationships. It can also rank the benefits of including each of the features, which helps in identifying the major spending patterns that affect specific personality traits.

3.4.3. Decision Tree (DT)

A DT splits data based on feature values into a tree-like graph, categorizing the data and showing rules that are more easily understandable. It recursively divides the data and constructs the tree in which every single node corresponds to a decision made based on the corresponding attribute value. For predicting personality types, these trees are very effective because they are efficient as well as easy to use. The significant shortcoming of Decision Trees is their ability to overfit and reduce generalization performance without pruning, a form of regularization.

3.4.4. Logistic Regression (LR)

It is a statistical method designed for multiclass classification and binary classification problems. It makes use of a logistic function to obtain predictions between the ranges of zero and one. Logistic Regression is straightforward yet provides an adequate foundation for predicting personality traits. It does have some restrictions, such as the assumption that there is a linear dependence between independent variables and the target class, which makes it harder to portray more complex behavioural patterns. While manually-crafted machine learning models like SVM, RF, DT, and LR produce valuable results, they often tend to fall short when analyzing the complex structures within data obtained from spending behaviour. For this reason, an optimized CNN architecture is deployed with a hierarchical structure. CNNs will be able to meaningfully identify spending behaviour patterns linked to personality traits. Research findings show us that the optimized CNN model (mentioned in section 3.3.5) is superior when it comes to any terms of comparing performance with machine learning algorithms. Table 1 shows the architecture of the optimized CNN.

3.4.5. Optimized CNN Architecture

Table 2 Detailed layer-wise architecture of the proposed 1D Convolutional Neural Network used for personality trait prediction from spending behaviour data. This 1D Convolutional Neural Network (CNN) is made to manage sequential or financial transactions effectively. This model concentrates on identifying significant patterns in one-dimensional data streams, in contrast to conventional 2D CNNs, which are tuned for image processing. The design can capture both low-level and high-level information since it has several Conv1D layers that gradually get more complicated. After every convolution layer, Batch Normalization is used to guarantee stable activations and speed up training by minimizing internal covariate changes.

Table 2. Detailed layer-wise architecture of the proposed 1D convolutional neural network used for personality trait prediction from spending behaviour data

Layer No.	Layer Type	Output Shape	Number of Parameters
1	Conv1D (ReLU)	(None, 95, 64)	256
2	Batch Normalization	(None, 95, 64)	256
3	MaxPooling1D	(None, 47, 64)	0
4	Conv1D (ReLU)	(None,47, 28)	24,704
5	Batch Normalization	(None,47, 28)	512
6	MaxPooling1D	(None,23, 28)	0
7	Conv1D (ReLU)	(None,23, 56)	98,560
8	Batch Normalization	(None,23, 56)	1,024
9	MaxPooling1D	(None,11,256)	0
10	Flatten	(None, 2,816)	0
11	Dense (ReLU)	(None, 512)	1,442,304
12	Dropout	(None, 512)	0
13	Dense (ReLU)	(None, 256)	131,328
14	Dropout	(None, 256)	0
15	Dense (ReLU)	(None, 128)	32,896
16	Dense Softmax)	(None, 7)	645

The model uses MaxPooling1D layers at different stages to increase performance. This helps downsample the feature maps and drastically lowers the number of calculations while maintaining important features. In contrast to a typical CNN, which can rely on deeper networks to accomplish comparable outcomes, this pooling technique avoids overfitting and expedites processing. To improve generalization and lower the danger of over-fitting, the model also incorporates Dropout layers in the fully connected part, which randomly deactivate neurons during training. The continuously decreasing structure of the fully linked (Dense) layers (512 → 256 → 128 → **7**) ensures the best possible balance between computing efficiency and feature representation. This model is meticulously designed to prevent duplicate calculations, in contrast to standard CNNs, which may have vast, thick layers that add needless complexity. The last layer is appropriate for classification problems as it produces predictions for five categories. The model consists of 1,698,485 parameters in total, of which 1,697,221 (99.9%) are trainable, indicating that nearly all of the parameters help in learning. While retaining a high training efficiency, the network is protected from overfitting by the use of Batch Normalization and Dropout layers. This architecture is a well-optimized option for personality prediction based on spending behaviour since it can achieve quicker convergence, lower memory use, and more accurate generalization than a standard CNN. The model may be even more effective with further improvements like adaptive learning rate scheduling, modifying dropout rates, or using Global Average Pooling rather than Flatten. Nonetheless, this CNN's present configuration offers a good compromise between computational simplicity and performance, which makes it a good model to analyse personality traits from spending data.

4. The Research Findings and Discussions

4.1. Individual Personality Trait Versus Category Profile Attributes

- Extraversion: Extraverted individuals tend to spend more on food, beverages, social activities, and transportation, while allocating comparatively less to groceries and supermarket purchases.
- Agreeableness: Individuals with higher levels of agreeableness tend to spend slightly more on charities. Furthermore, shows lower expenditure patterns in the categories of food, drink, and social entertainment.
- Conscientiousness: Individuals with high conscientiousness scores are likely to spend more on healthcare and less on gaming.
- Neuroticism: Spending on Personal Care and Beauty showed a positive relationship, while DIY-related expenditures exhibited a negative association.
- Openness: This trait has a negative correlation with household spending and a positive correlation with alcohol.

4.1.1. Materialism

Individuals with higher Materialism scores spend less on Charities and Postage/Shipping than their counterparts. There is a favourable association between the categories of food, drink, going out, and gambling.

4.1.2. Self-Control

Self-control was shown to be favourably associated with the categories of groceries and supermarkets, gas, and electricity, but negatively connected with mobile.

Figure 2 shows the correlation table, and the heatmap shows how expenditure trends correspond with behavioural inclinations and personality attributes. Spending on insurance has a substantial correlation (0.89) with neuroticism, indicating a risk-averse and worried personality where people look for financial stability.

Higher expenditure on food (0.14), transportation (0.12), and children (0.11) is associated with extraversion, suggesting a socially engaged lifestyle that includes going out to eat, traveling, and spending time with family. Charitable donations and agreeableness have a positive correlation (0.082), indicating a giving and selfless disposition. On the other hand, poor self-control is associated with higher gambling (-0.081) and mobile (-0.15) expenditure, indicating impulsive actions and trouble handling money.

4.2. Overall and Category-Related Features vs. Individual Traits

- Extraversion: Being extraverted. In comparison to their counterparts, more extroverted persons typically had more transactions (N_{tot}); also, we discovered a significant link with respect to the evolution of category similarity across time for the leading three expenditure categories ($C_{turnover(3)}$).
- Agreeableness: Being able to agree, there were no discernible relationships between this characteristic and the features we developed.
- Conscientiousness The Average Amount Per Transaction (A_{avg}) and the Total Amount Spent (A_{tot}) were found to be substantially and favourably connected with conscientiousness. Additionally, we discovered that those with greater Conscientiousness scores have more disparities in the proportional amounts spent over several weeks.
- Neuroticism: Being neurotic, the Average Amount Spent Per Transaction (A_{avg}), the Total Amount Spent (A_{tot}), and the Number of Spending Categories (N_c) were all lower for more neurotic people. Furthermore, we discovered a strong positive association with the burstiness of daily buying, with more neurotic individuals acting more impulsively toward their peers. • Openness to Experience: There is a positive correlation between N_{tot} and openness to experience; those who are more receptive to new experiences exhibit more impulsive pending and conduct more transactions than their counterparts.
- Materialism: In the top five spending categories, materialism was found to have a minor positive correlation with category similarity Over Time ($C_{turnover(5)}$). Additionally, we discovered a marginally inverse relationship with the typical transaction amount.
- Self-control: The Average Amount Per Transaction (A_{avg}) was higher for those who scored higher on the self-control scale. Figure 3 shows the correlation table of overall and category-related features vs. the personality trait correlation table.

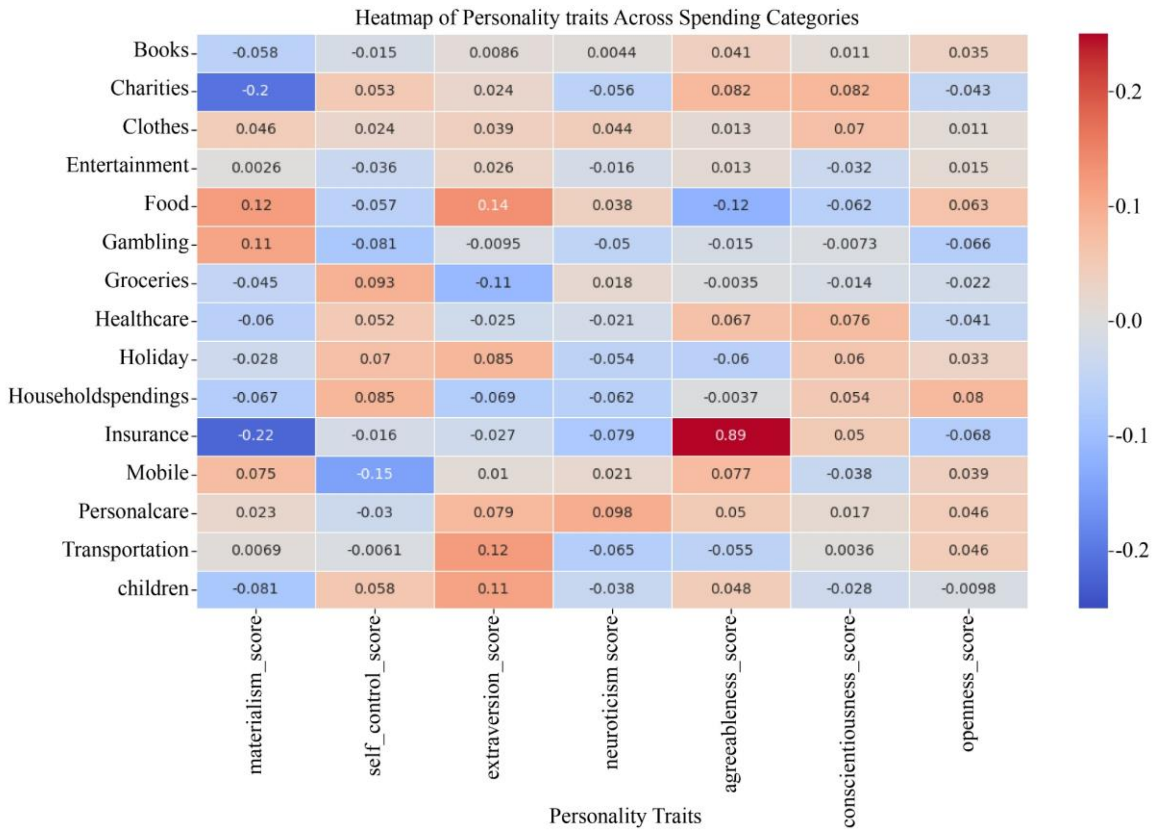

Fig. 2 Pearson correlation between individual characteristics and category profile attributes

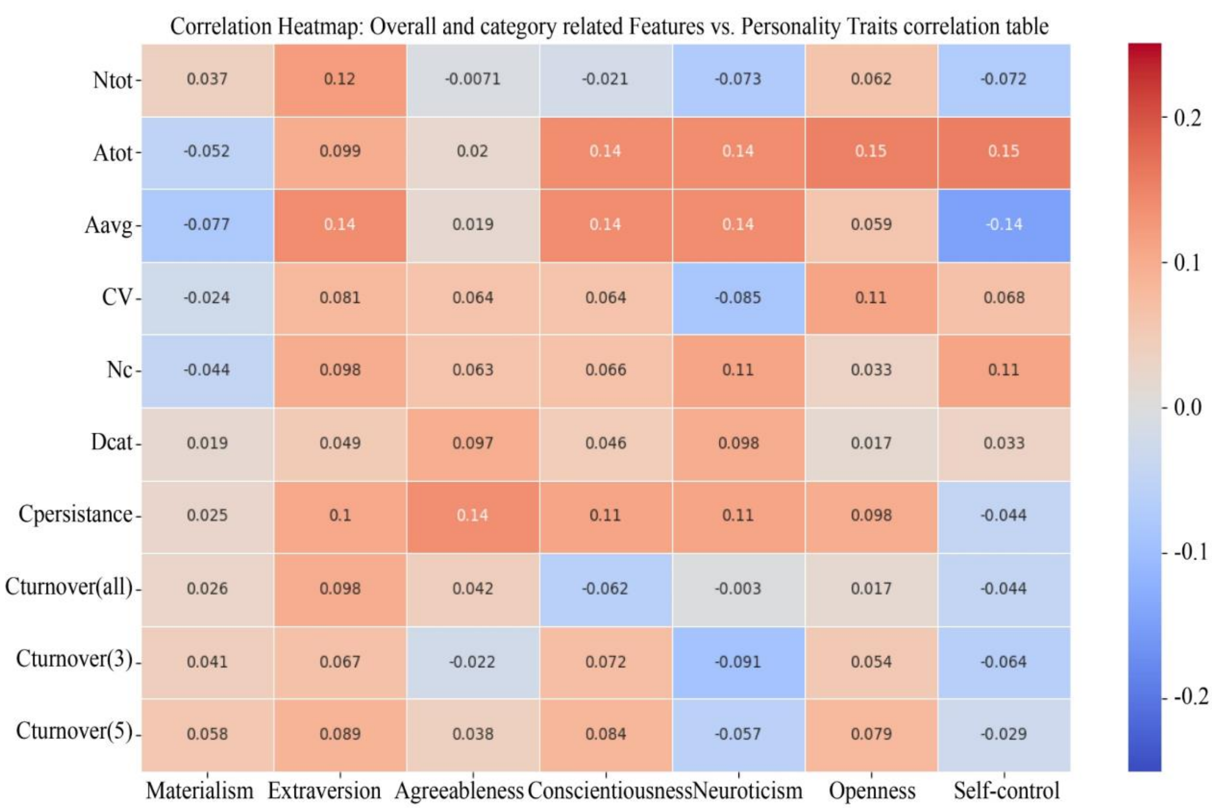

Fig. 3 Pearson correlation between overall and category-related features with individual traits

The heatmap illustrates how personality factors influence financial activities. Aavg (0.14) and Ntot (0.12) have a positive correlation with extraversion, suggesting that extroverts make more frequent and valuable transactions. Positive associations between conscientious people and Atot (0.14) and Aavg (0.14) indicate organized spending patterns. Nc (0.11) and Cpersistance (0.11), which represent recurring spending behaviors, are associated with neuroticism. On the other hand, Self-Control and Aavg have a negative correlation (-0.14), suggesting a relationship with impulsive expenditure.

4.3. Interpretation of Findings Based on Psychological Theories

The observed associations between spending behaviours and personality traits align closely with established psychological frameworks, particularly the Big Five Personality Model, along with the additional dimensions of materialism and self-control. Each trait reflects distinct motivational and emotional patterns that influence financial decisions. Extraverted individuals, being sociable and reward-seeking, tend to spend more on food, entertainment, and travel, reflecting their socially active nature.

Conscientious individuals, known for discipline and organization, direct more spending toward insurance, healthcare, and savings, indicating careful financial planning. Agreeable people show empathy and generosity, as seen in higher spending on donations and gifts. Neurotic individuals display emotional and impulsive spending patterns—especially in categories such as personal care, mobile, and gambling—often as a coping mechanism. Openness to experience, driven by curiosity and creativity, corresponds to higher expenditure on travel and cultural activities. Materialism is associated with increased spending on luxury and branded goods, emphasizing possessions and social status, while self-control shows the opposite pattern, with a greater focus on essentials like groceries and utilities and less impulsive spending. Interpretation of findings based on psychological theories is represented in Table 3.

Overall, these behavioural patterns confirm that consumer spending reflects underlying psychological traits. The proposed CNN model effectively captures these relationships, aligning its predictions with well-established psychological theories and prior research [2, 8, 13].

Table 3. Interpretation of findings based on psychological theories

Personality Trait	Observed Spending Pattern	Psychological Explanation
Extraversion	High on food, travel, and entertainment	Social and outgoing; seeks stimulation
Conscientiousness	High on insurance, healthcare, savings	Disciplined and goal-oriented
Agreeableness	More on charity and gifts	Empathy, kindness, and socially helpful behaviour
Neuroticism	Impulsive, personal care, and gambling	Emotional instability and stress coping
Openness	Travel, cultural events, and entertainment	Curiosity and creativity; seeks novelty
Materialism	Luxury, branded, non-essential items	Social status and self-enhancement motivation
Self-Control	Groceries, utilities, savings; low on impulsive spending	Discipline and delayed gratification

Table 4. Classification algorithms accuracy report

Classification models	Macro Average	Weighted average	Accuracy
SVM	0.83	0.82	81.50%
RF	1.00	1.00	100%
DT	1.00	1.00	100%
LR	0.74	0.74	76%

4.4. Comparative Performance and Outcomes of the Proposed CNN Framework

Before evaluating the proposed deep learning model, four classical machine learning algorithms, SVM, RF, DT, and LR, were trained and tested using the same dataset and feature set. Their performance metrics are presented in Table 4. The DT and RF models achieved the highest training accuracy of 100%, whereas SVM and Logistic Regression recorded 81.5% and 76% accuracy, respectively. Although these models demonstrated adequate baseline performance, the tree-based classifiers showed evidence of over-fitting. In contrast, linear models struggled to model the complex, non-linear patterns present in the behavioral data. Building upon these observations, the proposed optimized CNN was developed to overcome these limitations and to extract deeper hierarchical representations from transactional features.

The CNN model was successfully trained on the selected dataset, resulting in an impressive accuracy of 99.72%. As part of the assessment criteria, model performance and tendencies in accuracy and loss were scrutinized over a period of 20 training epochs. For comprehensive reporting, these are presented in Figures 4 and 5, which show the progress of the model during training.

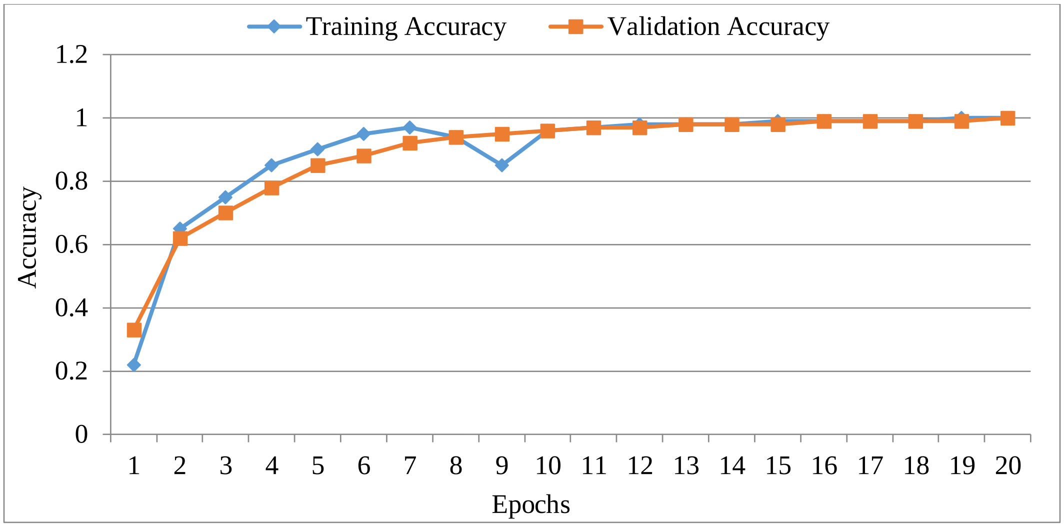

Fig. 4 Training and validation accuracy

The training and validation accuracy are shown in Figure 4-improvement over the 20 training epochs. There is an accuracy improvement with each subsequent epoch, which suggests that the model is able to learn important features from the data and is able to make predictions on new data. The increasing validation accuracy demonstrates the model's consistency and flexibility in predicting personality traits from spending patterns, with a relentless improvement. In Figure 5, the loss training and validation measures on accuracy over the 20 training epochs are depicted. It can be seen that losses in training and validation have, at best, reached a minimal level and have been maintained. The gradual downfall of loss speaks to the well-documented fact that as time goes by, the CNN model tends to facilitate lower amounts of errors in estimation.

This lowered statistic is understood to be a well-trained model where the feature extraction and classification capabilities of the model have improved over time, and the learning process has become optimized.

The results confirm the effectiveness of the proposed CNN model in predicting personality traits based on spending behaviour. By integrating convolutional layers with dropout regularization and a carefully optimized training strategy, the model achieves strong accuracy while maintaining excellent generalization to new data. The consistent increase in accuracy and decrease in loss further validate the robustness of the approach, demonstrating its potential for real-world applications in financial behaviour analysis and personality prediction.

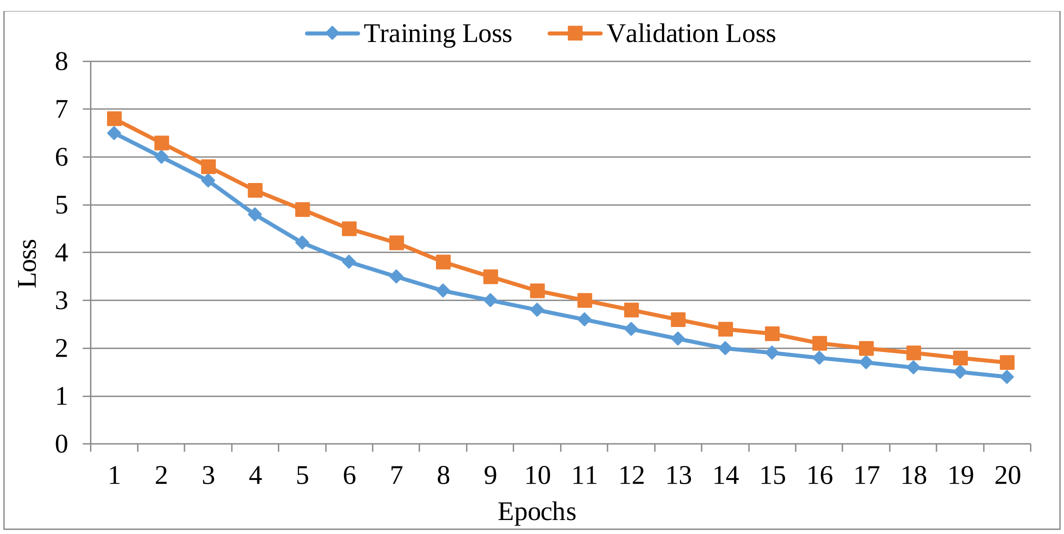

Fig. 5 Training and validation loss

The maximum accuracy achieved by the optimized CNN was 99.72%, verified by a 10-fold cross-validation process for generalization. Therein, the model always had above 98.5% accuracy in all folds and very low variance, confirming robustness and absence of overfitting. The close alignment between training and validation accuracy curves is shown in Figure 6. Additional metrics such as Precision (99.1%), Recall (98.7%), and F1-score (98.9%) indicated balanced performance across all personality traits. From a behavioural perspective, the model showed higher accuracy in predicting conscientiousness and extraversion, which are more strongly expressed in spending regularity and transaction frequency, whereas agreeableness and neuroticism displayed slightly lower precision due to contextual influences.

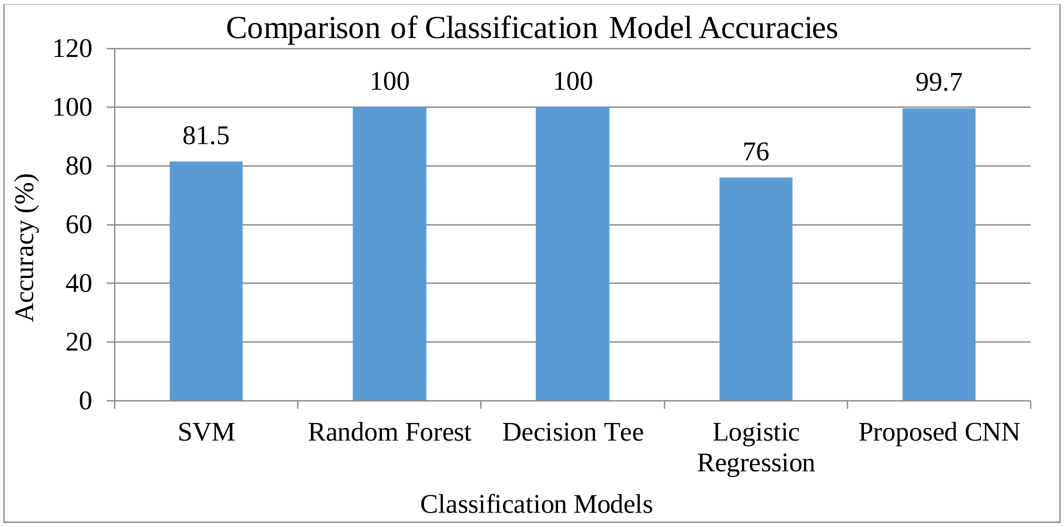

Fig. 6 Comparison of Classification Accuracies

Figure 6 shows the comparison of classification accuracies for SVM, RF, DT, LR, and the proposed optimized CNN model. The optimized CNN achieved 99.72% accuracy, by far outperforming the baseline models at predicting Personality traits from spending data. The optimized CNN outperformed the standard CNN. Because it effectively captures complex, nonlinear relationships in sequential spending data that traditional models fail to model, unlike Logistic Regression and SVM, which assume linear separability, or tree-based methods that the 1D-CNN often overfits the correlated features, learning hierarchical representations directly from raw transactional patterns. The convolutional layers in it extract both local and global spending behaviours, linking short-term impulsive purchases with long-term financial habits. The integration of Batch Normalization and Dropout improved generalization and prevented overfitting, whereas Pearson correlation–based Feature selection ensured that only psychologically and statistically relevant inputs were used. Together, these designs enabled the CNN to achieve 99.72% accuracy with strong cross-validation consistency, while distinctly outperforming state-of-the-art models by combining deep behavioural insight with robust learning efficiency.

4.5. Practical Implications

The personality prediction model based on CNN is one of the key applications in marketing and behavioural analytics. Marketers can plan their campaigns more effectively by using the information about how the personality traits of consumers affect their spending behaviour. Therefore, they can tailor marketing communication, optimize customer segmentation, and improve product recommendations. To illustrate, brands might customize offers for highly responsible consumers around savings and insurance, while at the same time, they could promote the extroverted or open-to-experience consumers with some experiential activities such as travel or entertainment. Behavioural specialists can take advantage of these revelations to gauge consumer well-being, facilitate financial planning, and analyze large-scale behavioural trends ethically by using anonymous data.

5. Conclusion

This paper presented an optimized Convolutional Neural Network-based model for predicting personality traits based on spending behaviour. The model efficiently processes transaction and behavioural data using deep learning techniques that attain a high accuracy of 99.72%. Training improvements over 20 epochs have been proven to be effective, efficient, and robust. The findings here suggest that the CNN learns complex multidimensional associations between financial behaviour and personality traits, further enhancing behavioural analytics.

It constitutes a valuable contribution to personality prediction and consumer analytics; at the same time, new directions could be opened for applications in personalized financial services, target marketing, and behavioural finance. Besides the methodological value, this research provides practical value to marketers and behavioural analysts by enabling data-driven customer segmentation, personalized campaigns, and objective consumer profiling. Potential future work might expand on this by adding more behavioural features, considering more sophisticated deep learning architectures, and assessing the robustness of the model using larger and more heterogeneous data sets. Moreover, embedding techniques for explainable AI and addressing ethical concerns about privacy and consent will be crucial for the deployment of such a system in real-world applications.

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