Voice Centric Personality Evaluation in Children

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Abstract
A speech-based personality assessment for children is a method of evaluating a child's personality traits by analyzing patterns in their speech, using artificial intelligence to extract cues like tone of voice, word choice, and speech rate to infer personality characteristics like extroversion, agreeableness or emotional stability, offering an alternative to traditional personality tests that might not be suitable for young children due to their unique communication styles. The proposed system aims to develop an automatic children's personality assessment from emotional speech using Convolutional neural networks (CNN). The system analyzes a child's emotional speech to identify their personality traits in less time compare to other traditional methods.

Keywords: Convolutional neural network, Children's Personality Questionnaire, MXNet, Tensorflow and Voice Centric Personality.

Introduction:
Personality represents the collection of emotional, behavioral, and cognitive patterns that make each individual unique. It influences how people respond to situations and interact with others, and it can help predict future behavior. Assessing personality, however, is particularly challenging in children because their psychological, emotional, and social traits are still developing. While traditional frameworks like the Big Five Personality Model are well established for adults, they often fail to capture the fluid and evolving nature of children's personalities. To address this, psychologists have developed child-specific assessment tools such as the Children's Personality Questionnaire (CPQ) and the Murphy–Meisgeier Type Indicator for Children, which help evaluate emotional and behavioral tendencies during early development. Since children's personalities are shaped by both innate factors and environmental experiences, understanding them at an early stage can assist educators and psychologists in supporting learning, social adjustment, and emotional well-being. Recently, advancements in technology—especially speech analysis and artificial intelligence—have introduced new possibilities for personality assessment, providing a more natural, objective, and less intrusive way to evaluate children compared to conventional testing methods.

Literature Survey
Automatic personality assessment has emerged as a promising alternative to traditional questionnaire-based methods, which often suffer from subjectivity, response bias, and limited scalability. Recent

studies have explored the use of behavioral and paralinguistic cues—such as speech and movement—to infer personality traits in an objective and unobtrusive manner.

Pérez-Espinosa et al. proposed an automatic system for assessing children's personality traits using emotional speech signals. Their study focused on children aged between 8 and 12 years, highlighting the importance of personality identification in enhancing teaching–learning strategies and detecting early psychopathological indicators. Instead of relying on self-reported questionnaires, the authors analyzed acoustic features extracted from children's voices recorded during playful interactions with peers and a social robot. A dataset comprising 98 children was developed and annotated with five paralinguistic labels. Using these labels, multiple classification models were trained to identify both primary and secondary personality traits as defined by the Children's Personality Questionnaire. The results demonstrated high feasibility of speech-based personality estimation, achieving an F-score of 0.89 for extroversion and 0.79 for excitability, while anxiety achieved a moderate F-score of 0.70. The study concludes that emotional speech analysis can serve as an effective and transparent tool for automatic personality assessment in children.

Delgado-Gomez et al. investigated personality assessment through movement analysis, addressing the limitations of traditional psychometric tools such as cultural bias and response unreliability. Their approach utilized body movement data captured using a low-cost Microsoft Kinect sensor, making the system practical and accessible. A multiple linear regression model was developed to predict personality traits based on movement patterns, following the Big Five Personality Model. A pilot study revealed that extroversion and conscientiousness showed the strongest correlations with movement features. Additionally, distinct movement patterns associated with each of the five personality traits were identified. The findings validate the feasibility of using motion-based behavioral cues for personality assessment and highlight its potential applications across education, healthcare, sports, and organizational contexts.

Polzehl, Möller, and Metze presented one of the early studies on automatic personality assessment from speech, comparing human perception with machine-based classification. In their work, a professional speaker was instructed to produce speech reflecting different personality profiles aligned with the Big Five (NEO-FFI) traits. Human evaluators, unaware of the speaker's intended personality cues, were asked to assess the traits based solely on speech samples. Acoustic and prosodic features were extracted and analyzed using signal-based methods. The study found a high degree of consistency between the acted personalities, human judgments, and automatic classification results. These findings provided early evidence that personality traits can be reliably inferred from speech signals and laid the foundation for future personality-aware human–machine interaction systems.

Overall, the reviewed studies collectively demonstrate that personality traits can be effectively inferred from non-intrusive behavioral data such as speech and movement. These approaches offer objective, scalable, and user-friendly alternatives to conventional assessment methods and open new research avenues for adaptive and personalized human–computer interaction systems.

Comparative Analysis of Existing Works vs. Proposed System

Criteria	**Pérez-Espinosa et al. (2021)**	**Delgado-Gomez et al. (2022)**	**Polzehl et al. (2010)**	**Proposed MFCC + CNN System**
Target	Children (8–12	Adults (pilot study)	Professional	Children (emotional

Criteria	Pérez-Espinosa et al. (2021)	Delgado-Gomez et al. (2022)	Polzehl et al. (2010)	Proposed MFCC + CNN System
Population	years)		speaker, human raters	speech)
Data Modality	Speech during child–child and child–robot interactions	Body movements captured using Kinect	Acted speech with personality cues	Emotional speech recordings
Features Used	Acoustic + prosodic features; paralinguistic labels	Movement-based behavioural features	Acoustic & prosodic features	MFCCs (spectral features)
Model Used	Conventional ML classifiers	Multiple linear regression model	Initial automatic classifiers; human comparison	Convolutional Neural Network (CNN)
Personality Framework	Children's Personality Questionnaire (primary & secondary traits)	Big Five Personality Model	Big Five Personality Traits	Can be adapted to Big Five or CPQ
Key Findings	High accuracy for extroversion & excitability (F-score: 0.89, 0.79)	Strong predictions for extroversion & conscientiousness	Consistent detection of personality from vocal patterns	Expected improved accuracy via deep feature learning
Strengths	Real children dataset; robot-mediated interactions	Low-cost hardware; motion-based cues	Validates speech cue relevance; human-machine comparison	Deep learning; robust representation; automatic feature extraction
Limitations	Relies heavily on labelled paralinguistic cues	Limited personality coverage; small pilot sample	Acted speech lacks natural variability	Requires larger dataset; computationally intensive
Innovation Level	Moderate—extends child interaction studies	Moderate—introduces motion analysis	Foundational—early speech-based trait study	High—first MFCC + CNN pipeline focused on children's emotional speech
Real-Time Applicability	Limited	Possible but not explored	Not designed for real-time	High—CNN allows fast inference for live assessment
Objective	Semi-automated	Highly objective	Human involvement	Fully automated and

Criteria	Pérez-Espinosa et al. (2021)	Delgado-Gomez et al. (2022)	Polzehl et al. (2010)	Proposed MFCC + CNN System
Measurement			still significant	reproducible

Technology Survey:

A technology survey is a structured examination and analysis of various technologies or tools within a specific field or industry. Its primary objective is to gather information on different technological options, comprehensively understand their features, capabilities, limitations, and assess their suitability for a specific purpose or project.

By conducting a technology survey, individuals or organizations can explore a range of available technologies and make well-informed decisions regarding the adoption or selection of the most suitable technology for their needs. It involves a systematic process of evaluating and comparing technologies to identify the best fit based on factors such as functionality, performance, compatibility, cost, and scalability.

Machine Learning

Machine learning is a field of study where computer algorithms are designed to enable computers to learn and make predictions or decisions without being explicitly programmed for each task. It involves training computers to learn from examples and experiences, allowing them to automatically identify patterns and make accurate predictions based on data.

To accomplish this, large amounts of data are fed into the computer, along with algorithms or rules that enable it to analyze and learn from the data. Through this process, the computer becomes adept at recognizing patterns, establishing relationships, and making predictions or taking actions when presented with new or unfamiliar data. Essentially, it is akin to teaching a computer to recognize patterns and make predictions by exposing it to numerous examples.

Machine learning finds application in various aspects of our daily lives, including voice recognition, image classification, recommendation systems, fraud detection, and even self-driving cars. Its potential lies in automating tasks, enhancing decision-making processes, and improving overall efficiency. By harnessing the power of machine learning, computers are empowered to learn from data, continually improve their performance, and assist us in solving intricate problems and making informed decisions.

Python Language

Python has emerged as one of the most favored programming languages for machine learning due to its extensive range of libraries and frameworks tailored specifically for this field. Python offers a multitude of tools and resources that greatly simplify the implementation of machine learning algorithms and workflows.

Python's machine learning ecosystem boasts several key features:

Python is widely used in machine learning due to its rich ecosystem of libraries and frameworks. Tools such as **scikit-learn** support data preprocessing, feature selection, model training, and evaluation, while **TensorFlow**, **PyTorch**, **Keras**, and **MXNet** enable deep learning and neural network development. For data handling, **NumPy** and **pandas** provide efficient numerical computation and data manipulation capabilities. Visualization libraries like **Matplotlib** and **Seaborn** assist in data exploration and performance evaluation through effective graphical representations. Python also benefits from a strong and active community that offers extensive documentation, tutorials, and reusable code. Additionally, it integrates seamlessly with databases, big data platforms, and web frameworks, making it suitable for end-to-end machine learning development and deployment.

Python IDLE

Python IDLE (Integrated Development and Learning Environment) is an integrated development environment (IDE) bundled with Python. It offers a user-friendly interface for writing, running, and testing Python code, making it ideal for beginners.

Python IDLE provides several notable features:

Editor: Python IDLE includes a built-in text editor that supports syntax highlighting, indentation assistance, and auto-completion. These features enhance code writing by reducing errors and improving productivity.

Interactive Shell: The interactive shell is a standout feature of Python IDLE. It allows you to execute Python code line by line, providing immediate feedback on the output. This feature is helpful for experimenting, testing code snippets, and exploring Python interactively.

Debugger: Python IDLE incorporates a debugger tool that aids in identifying and resolving errors or bugs in code. It enables you to step through the code, set breakpoints, and examine variable values during execution, facilitating troubleshooting and understanding of program flow.

Code Execution: Python IDLE allows you to run your code directly from the editor or the interactive shell. It offers options to execute the entire script or specific portions, simplifying testing and debugging processes.

Help and Documentation: Python IDLE provides access to extensive documentation and help resources. It offers context-sensitive help, allowing users to access relevant documentation for Python language features, libraries, and functions. It also provides browsing capabilities for official Python documentation.

Python IDLE serves as a lightweight and beginner-friendly IDE, enabling users to write, execute, and explore Python code. It offers a simple interface with useful features for coding, debugging, and learning Python programming. While it may lack advanced functionalities found in other IDEs, Python IDLE remains a convenient choice for beginners and basic coding tasks.

Flask Web kit Framework

Flask is a widely used Python web framework known for its simplicity and flexibility. It enables developers to swiftly and effectively construct web applications. Flask adheres to the Model-View-Controller (MVC) architectural pattern and offers a plethora of tools and libraries to handle diverse web development tasks.

The framework provides essential features such as URL routing, template rendering, request management, session handling, and database integration. Its minimalistic design empowers developers to selectively incorporate and combine components based on their specific project requirements. Flask boasts an active community and comprehensive documentation, making it a favored option for creating web applications of varying sizes and complexities.

Time Complexity

Audio Processing: The complexity of processing audio inputs to extract relevant features like speech patterns, tone, emotions, and linguistic content can affect the overall time complexity.

Machine Learning Models: If the project involves using machine learning models for personality assessment, the time complexity will depend on the algorithms used, the size of the training data, feature extraction methods, and model training and inference times.

Real-Time Processing: If the system requires real-time processing of speech inputs, such as in interactive assessments or live feedback scenarios, the time complexity will be influenced by the need for quick response times and efficient processing pipelines.

Scalability: The scalability of the system, i.e., its ability to handle increasing numbers of users or concurrent assessments, can also impact time complexity. Efficient design and utilization of resources such as parallel processing or distributed computing can mitigate scalability-related complexities.

Feasibility Study

A feasibility study is an in-depth examination of the project that will be implemented. It examines all aspects of the project to determine whether or not it will succeed. It is useful in determining whether the project is feasible, whether there are any technical issues, and whether it will take too long to complete. It assists project participants in making decisions. It assists them in deciding whether to proceed with the project, make changes to it, or choose a different project.

Economic Feasibility

The term "economic feasibility" refers to determining whether or not a project idea is financially viable and worthwhile. It entails analyzing the project's costs and assessing the potential benefits it can generate. Identifying the resources required, such as materials, equipment, software, or any specialized assistance, is part of this process. Benefits could include new knowledge, academic recognition, skill enhancement, or contributions to the field of study. Furthermore, any potential risks or challenges that could affect the project's financial feasibility must be considered. These may include unanticipated expenses, limited funding or resources, or time or expertise constraints. Assessing and addressing these risks in advance will contribute to a more accurate assessment of the project's economic feasibility.

Technical Feasibility

This determines whether the project can be technically implemented. It focuses on determining whether the necessary technology, tools, and expertise are available to complete the project successfully. It evaluates the availability and suitability of the necessary technology, infrastructure, and expertise. It also considers any technical constraints or challenges that may arise during project execution. The research identifies potential problems and suggests solutions.

Operational Feasibility

It refers to determining whether a project can be implemented and operated in a practical and efficient manner. It entails assessing the day-to-day aspects and feasibility of completing the project successfully. The operational feasibility of a project takes into account factors such as the availability of resources, skills, and personnel needed to complete the project. It entails determining whether the project will have access to the necessary materials, facilities, and human resources. Furthermore, operational feasibility investigates whether the project is compatible with existing processes and procedures. It considers any potential operational challenges, dependencies, or risks that may impact your project's implementation and operation. This analysis ensures that the project is feasible, achievable, and compatible with the available resources and operational environment.

System Architecture

System architecture refers to the conceptual design and structure of a software system. System architecture provides a high-level view of how the system is structured and how its components work together to achieve the desired functionality and meet the specified requirements.

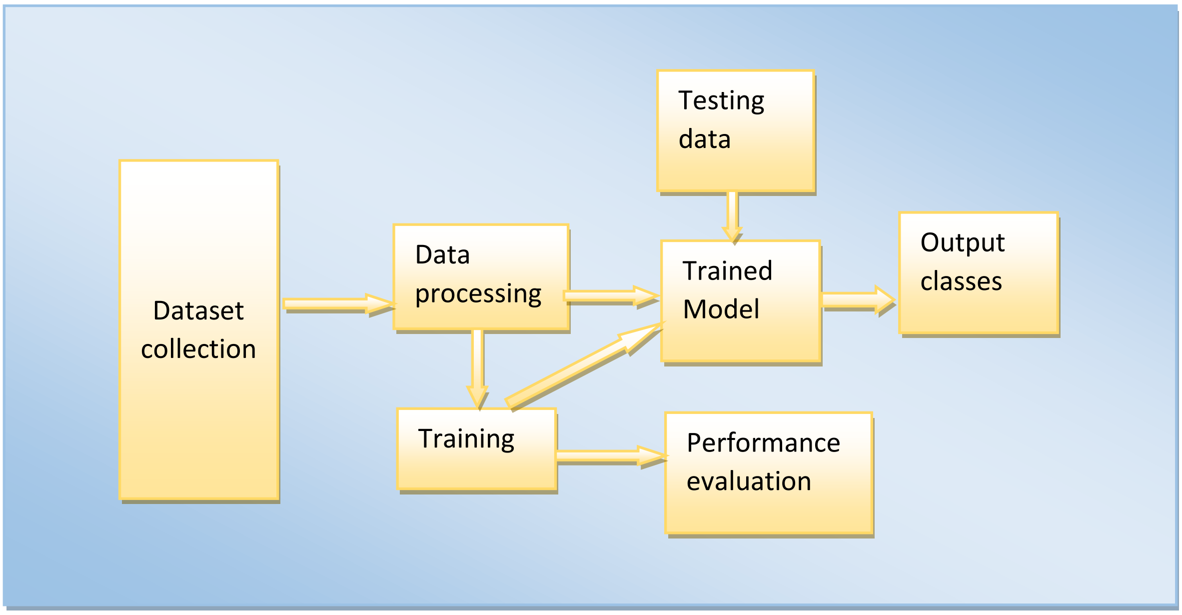

Fig 1:

Implementation

Adopted Approach

The proposed system will use a database of emotional speech signals recorded from children to train a CNN model. The speech signals will be pre-processed to remove background noise and resampled to a fixed length. The Mel-frequency cepstral coefficients (MFCCs) will be used to extract the features from the speech signal. The extracted features will be fed into the CNN model to identify the child's personality traits. The performance of the proposed system will be evaluated using accuracy, sensitivity, specificity, and the area under the receiver operating characteristic curve (AUC-ROC).

System testing

Testing Approach: Software testing is a crucial process in the software development lifecycle that involves evaluating a software system or application to ensure its quality, functionality, and reliability. The goal of software testing is to identify defects, errors, or inconsistencies in the software and ensure that it meets the specified requirements.

Unit Testing: Unit testing is the process of testing individual components or units of a software system in isolation. In this type of testing, each unit, which can be a function, method, or class, is tested independently to ensure that it behaves as expected. Unit tests typically focus on testing the functionality, inputs, and outputs of the unit being tested. Mock objects or stubs may be used to simulate the behavior of dependencies. Unit testing helps identify bugs or issues within specific units of code and facilitates easier debugging and maintenance. It provides developers with confidence in the correctness and reliability of their individual units of code.

Integration Testing: Integration testing involves testing the interaction and collaboration between different components or units of a software system. It ensures that the integrated components work together seamlessly and perform their intended functionalities. Integration testing can be performed at different levels, such as integration between modules, services, or subsystems. The purpose of integration testing is to detect any interface or communication issues between the components, ensure proper data flow, and validate the overall system behavior. It helps identify defects or inconsistencies that arise when multiple components interact with each other.

System Testing: System testing is a comprehensive testing phase that evaluates the behavior and functionality of a complete software system. It tests the system as a whole, considering all integrated components, subsystems, and external dependencies. System testing verifies that the system meets the specified requirements and works correctly in different scenarios, configurations, and environments. It includes functional and non-functional testing, such as performance testing, usability testing, security testing, and compatibility testing. System testing is usually performed from an end-user perspective to ensure that the software meets the intended objectives and delivers the desired functionality.

In summary, unit testing focuses on testing individual units of code, integration testing verifies the interaction between components, and system testing validates the behavior and functionality of the complete software system. These testing levels work together to ensure the quality, reliability, and proper functioning of the software throughout its development and deployment lifecycle.

Test Cases

TEST CASE NUMBER	INPUT	EXPECTED OUTPUT	ACTUAL OUTPUT	RESULT
1.	Psychiatric Data Managers logs in to the system using a valid email and password combination for authentication and access purposes.	Login is successful	Login is successful	Pass
2.	The Psychiatric Data Managers chooses the audio dataset and proceeds to upload it into the system.	Dataset is uploaded successfully and is available for training	Dataset is uploaded successfully and is available for training	Pass
3.	The Psychiatric Data Managers performs the action of saving the trained model for future use.	Model is saved successfully	Model is saved successfully	Pass

4.	Psychiatric Data Managers provides training memo and saves it	Training Memo is saved successfully	Training Memo is saved successfully	Pass
5.	Clinical Research Coordinator provides valid email and password for login purpose	Login is successful	Login is successful	Pass
6.	The Clinical Research Coordinator uploads an image and verifies the corresponding output for evaluation and analysis.	Output and the results are displayed successfully	Output and the results are displayed successfully	Pass
7.	The Child Life Specialists registers an account by entering their email, username, and password details.	Account is created successfully and the data is stored in the database server	Account is created successfully and the data is stored in the database server	Pass
8.	Child Life Specialists logs in by providing valid email and password	Child Life Specialists can login successfully	Child Life Specialists can login successfully	Pass
9.	Child Life Specialists uploads a test audio for testing	Child Life Specialists detection is successfully	Child Life Specialists detection is done successfully	Pass

Conclusion

The proposed system aims to provide an automatic children's personality assessment from emotional speech using CNN. The system will extract features from a child's emotional speech signal to identify their personality traits. The proposed system has several advantages over traditional methods of personality assessment, including being less time-consuming, more objective, and providing real-time feedback on a child's emotional state. The proposed system has the potential to revolutionize the way children's personalities are assessed in therapeutic and educational settings

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