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DATA MINING PROCESS

The data collection process leverages state-of-the-art yet focused methods targeting devices with less robust security measures. The cornerstone of this approach is **Unexposed Small Routines Codes Carrier via Brute Force**, operating as Spyware deployed through a Malware Carrier. The objective is to **discreetly** integrate compact code sequences into the designated device **for the covert acquisition of unfiltered data.**

To fulfill this, we utilize a specialized **Remote Access Trojan,** dubbed RAT-Massive. This RAT shows particular efficacy on open-source platforms such as Android, most notably when these devices are connected to networks with less stringent security.

The strategic deployment of this targeted code takes place through Base Transceiver Stations (BTS), capitalizing on less fortified data transaction pathways. This strategy shows elevated effectiveness when **piggybacking on the existing infrastructure**, notably in the context of the Palapa Ring Project.

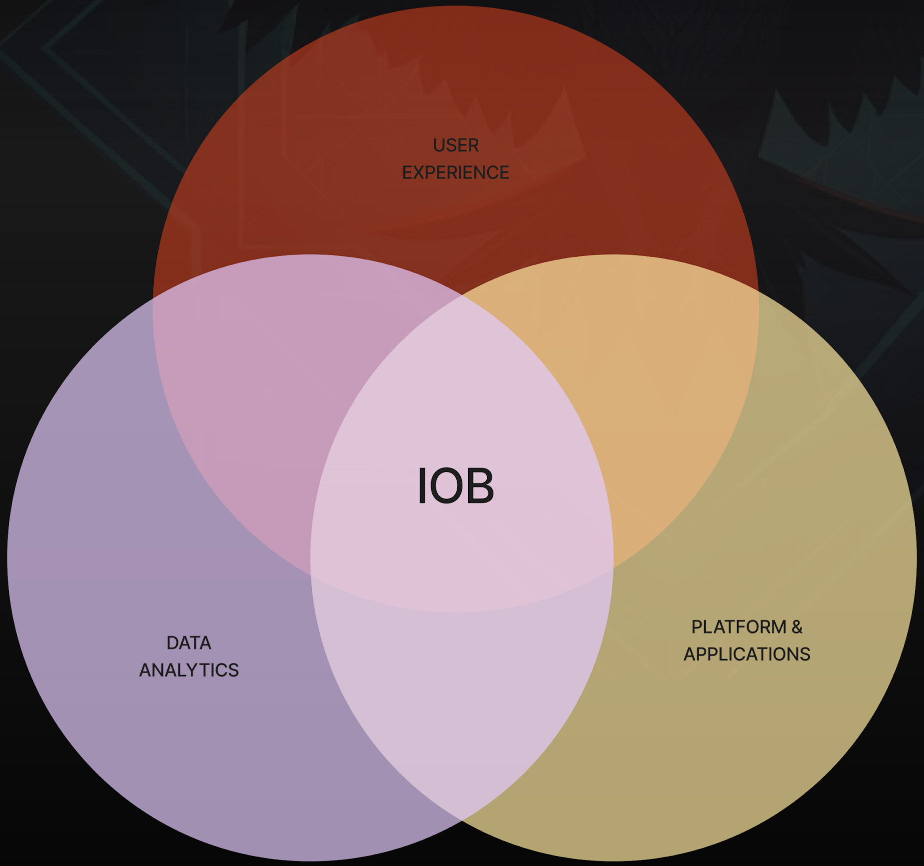
It's important to clarify that this approach sees diminished effectiveness against systems fortified with higher-level security protocols, such as Apple's iOS and Huawei's proprietary operating system.

In summary, the overarching goal of this methodology is to **acquire unfiltered data for the greater good**, albeit with constraints concerning the types of devices that can be targeted.

INTERNET OF BEHAVIOUR (IOB)

Internet of Behaviors (IOB) via Terra-Logic Engine

Represents a sophisticated analytical framework that continuously captures user data around the clock. This data is accumulated from what we term as 'digital dust,' essentially the residual digital footprints such as cache and browsing history left by users during their day-to-day interactions with electronic devices. This automated 24/7 data collection offers valuable insights into both internet usage patterns and subsequent behaviors, presenting a rich resource for advanced behavioral analytics



NATURAL LANGUAGE PROCESSING

Natural Language Processing (NLP) operates as a sub-discipline within the expansive domain of Artificial Intelligence (AI), focusing specifically on enhancing machine capabilities for comprehending human-generated linguistic constructs. The objective is not merely to interpret syntax but to achieve a nuanced understanding that allows for contextually accurate responses.

By converging methodologies from linguistics and computer science, NLP algorithms are engineered to distill semantic and syntactic value from textual sequences, thereby enabling AI systems to anticipate or predict conversational context with increased precision.

When breaking down the computational algorithms employed in machine learning for data parsing and interpretation, several key methodologies are pivotal: (Next Page)

NATURAL LANGUAGE PROCESSING

- **Lexical Analysis** This foundational stage involves dissecting the syntactical elements of a language into its basic units, often referred to as 'tokens' or lexemes. The compilation of these units forms the lexical repository or lexicon of a particular language.
- **Syntactic Analysis (Parsing)** At this juncture, parsing algorithms play a critical role in classifying and organizing the lexemes into a hierarchical structure that depicts grammatical relations among the words.
- **Semantic Analysis** Beyond syntax, semantic analysis aims to decode the intrinsic meanings of lexical elements by linking syntactic structures and objects to their corresponding conceptual entities within a specified task domain.
- **Discourse Integration** This phase involves co-reference resolution and discourse linking. In simpler terms, the semantics of each sentence are evaluated in the context of preceding and succeeding sentences to ensure narrative coherence and contextual relevance.
- **Pragmatic Analysis** Pragmatic analysis is a form of high-level interpretation that focuses on deriving intended meanings, which may involve extralinguistic context or inference-based reasoning. This often requires algorithms that are capable of simulating human-like common sense and real-world knowledge.

By incorporating these methodologies, the system can be more adept at identifying linguistic anomalies, interpreting user intent, and assessing potential security risks within natural language data streams.

NATURAL LANGUAGE PROCESSING

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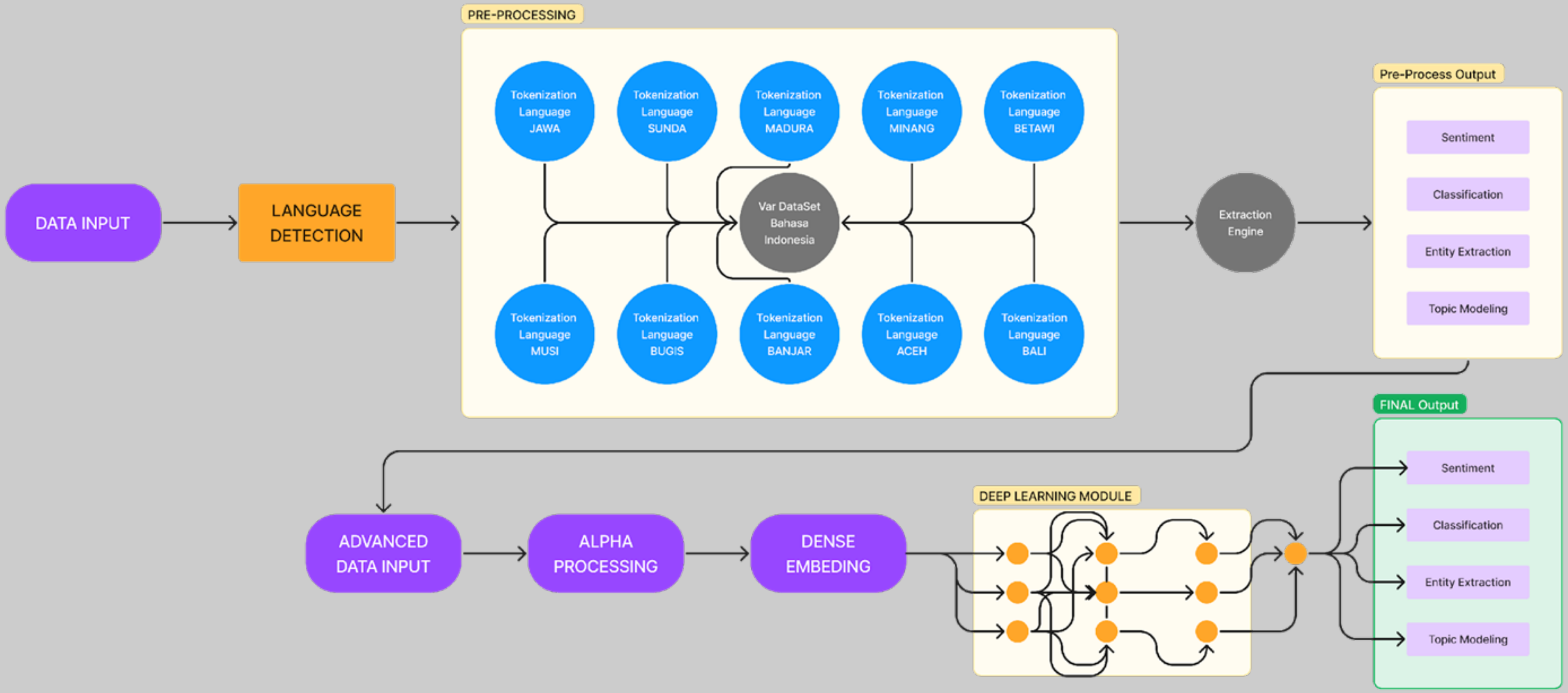


FACE RECOGNITION

Our facial recognition system employs Google Optical Flow Programming and TensorFlow to delve deeply into macro and micro-expressions (fig.1), thereby offering unparalleled behavioral analytics capabilities. **The machine learning engine *meticulously filters*** and studies these **expressions** *harvested from a spectrum of device users*, **subsequently feeding them into an advanced Deep Learning algorithm that executes complex mathematical computations for a nuanced understanding of dynamic emotional responses.**

To elevate this technology, we've seamlessly integrated ***Google Optical Flow capabilities***—*widely recognized in daily experiences for object recognition functions such as Google Lens*. This integration fortifies the algorithm's precision, transforming it into a robust, all-encompassing recognition system.

Our methodology also capitalizes *on **OpenCV (Open Source Computer Vision Library)**, an invaluable asset with a repository of billions of categorized facial expressions.* This strategic implementation not only fortifies the recognition algorithm but also enables culturally-sensitive calibrations. ***In particular, our technology has been enriched with data pertaining to Indonesian facial features, thereby boosting its adaptability and localization accuracy.***

Study References & Citation

https://www.tensorflow.org/overview

https://research.google/pubs/pub50576/

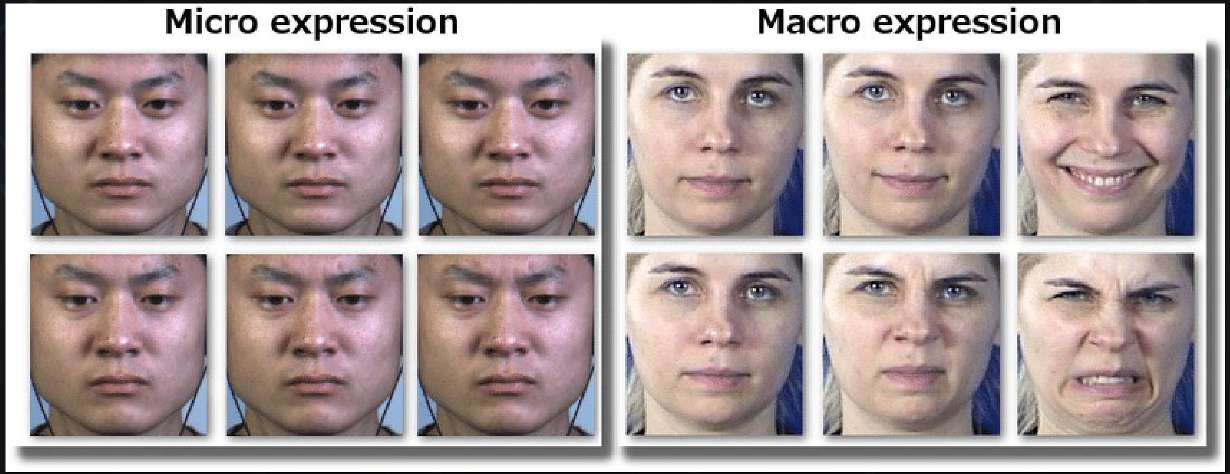


Fig.1

Core Data Processing Concepts:

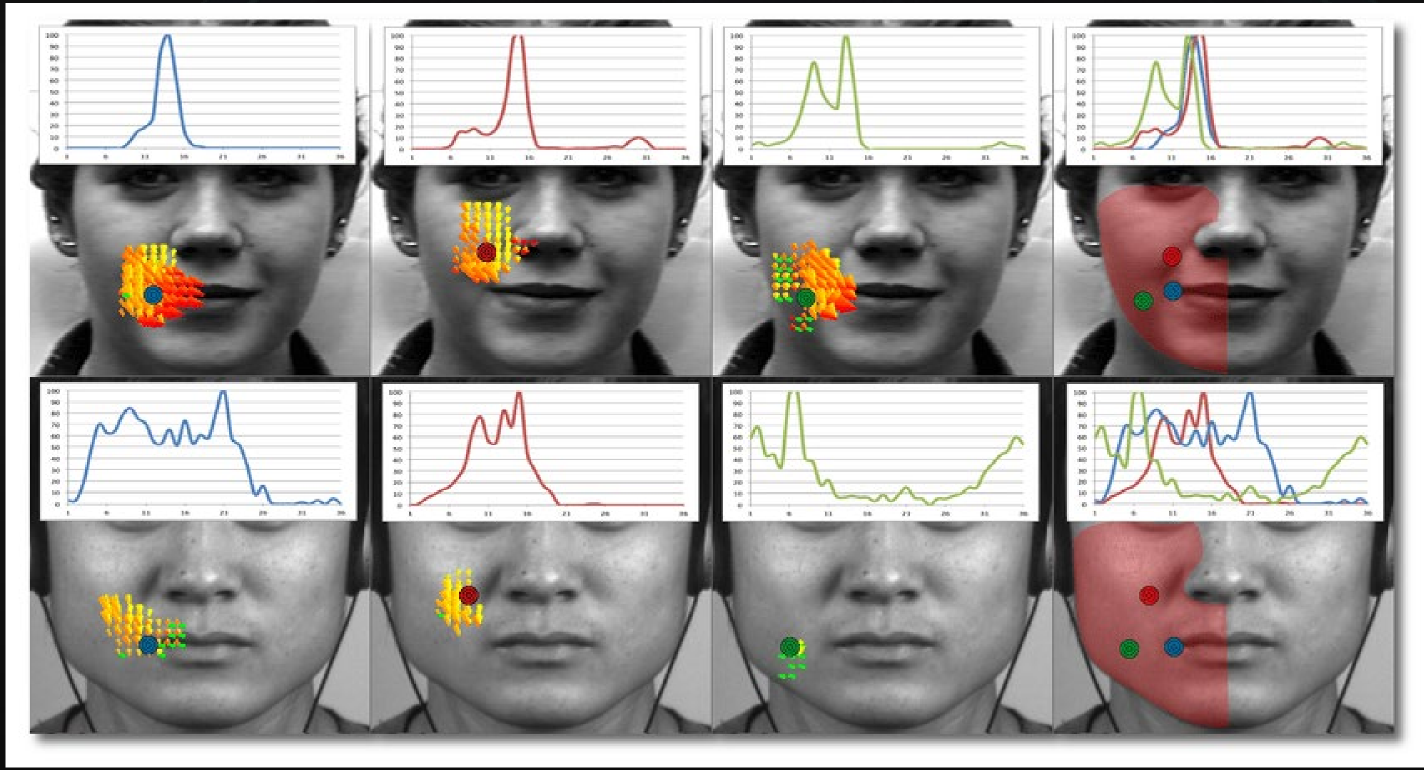
At the heart of this technology lies a multi-faceted data processing pipeline

1. **Optical Flow Programming** captures facial nuances with high precision.
2. **TensorFlow's Deep Learning algorithms** dive into complex emotional landscapes, extracting both overt (macro) and subtle (micro) emotional cues.
3. **Machine Learning Engines** provide the initial interpretive layer, identifying and sorting facial expressions based on pre-defined criteria.
4. **Deep Learning Engines** engage in higher-order emotional classification, utilizing mathematical models that adapt dynamically based on incoming data.

FACE RECOGNITION

We've deployed a cutting-edge facial expression recognition method that hinges on the innovative feature of **Local Motion Patterns (LMP).**

The LMP features locally analyze motion distribution to separate consistent movement patterns from background noise. Indeed, facial movements extracted generally contain noise and, without specialized processing, fall short of meeting the rigorous requirements for expression recognition, particularly for micro-expressions. Both the direction and magnitude of movements are statistically profiled to filter out noise.



Study References & Citation

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https://research.google/pubs/pub50576/

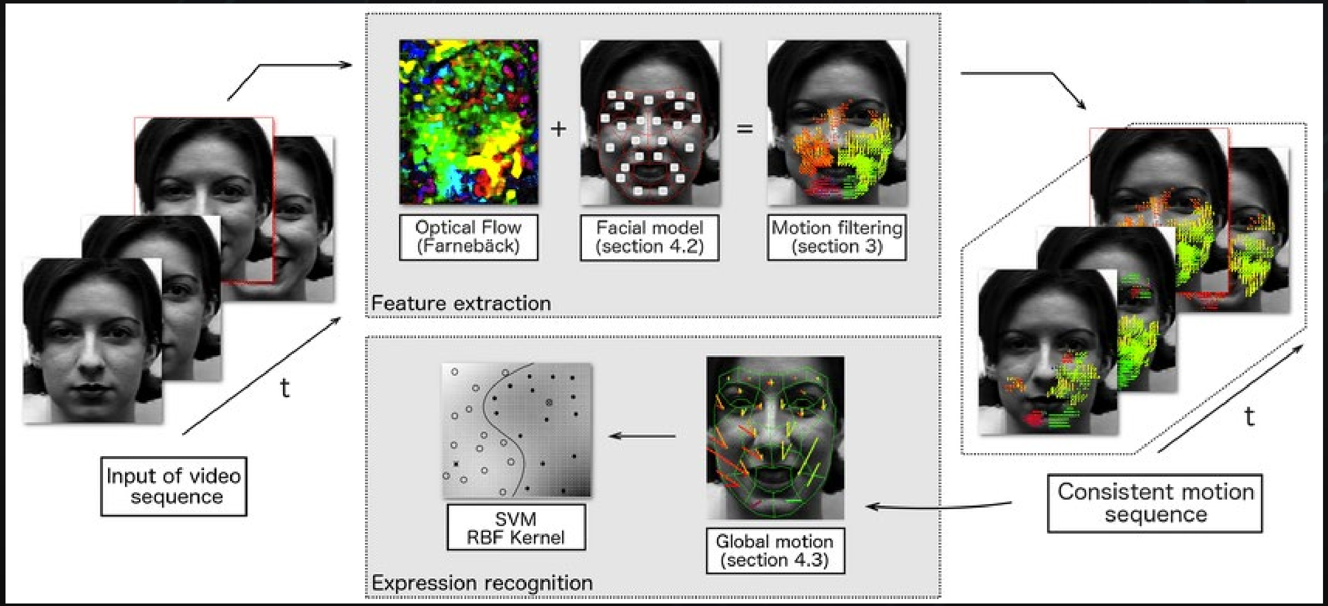
FACE RECOGNITION

This AI-driven methodology makes three critical contributions:

1.It conducts an in-depth analysis of the temporal elasticity and deformations of facial skin during various expressions.

2. introduces an integrated approach (openCv + Developer Data training Indonesian Faces) for recognizing both macro and micro-expression datasets, vital for accommodating an extensive range of emotional intensities.

3. Innovative strides towards 'in-the-wild' facial recognition, surmounting challenges such as variable expression intensities, intricate activation patterns, and nuanced head pose variations



In essence, our method aims to **capture unfiltered, raw emotional data for the greater good**, overcoming several challenges that hinder accurate expression recognition in real-world settings.

Study References & Citation

https://www.tensorflow.org/overview

https://research.google/pubs/pub50576/

AI-DRIVEN PERSONALITY INSIGHTS

Using Hierarchical Clustering

RAVENSTONE
REFERENCE DECK.

Introduction

This model aims to construct a personality prediction system using an unsupervised learning approach. It leverages Big Data, processed into the Indonesian language in unlimited quantities. Agglomerative hierarchical clustering is chosen to build a personality prediction model based on the content and context from various data sources like social media, internet behaviors, facial expression recognition (both macro & micro-expressions via Face Recognition Technology), and the application of NLP (Natural Language Processing) in several regional languages in Indonesia.

These languages are then understood and translated into Indonesian by Deep Learning and AI technologies. This model has an accuracy rate of 79.99% with an average silhouette score of -0.3. It can handle vast amounts of data, running ceaselessly 24/7.

OCEAN

Personality traits are inherent qualities of an individual formed by their thought patterns, emotions, and behavior. There are five key categories in the Big Five Personality Traits: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Automated personality testing methods have emerged through the analysis of conversations using NLP.

Automatic measurement of personality by utilizing linguistic features from social media text is another cost-effective method compared to manual measurements. Machine learning has been successfully employed to gauge the personality of social media and forum users using methods like Naïve Bayes and clustering techniques, which rely on supervised learning.

Study Ref. Jeremy, N. H., Prasetyo, C. dan Suhartono, D., "*Identifying personality traits for Indonesian user from twitter dataset,*" *International Journal of Fuzzy Logic and Intelligent Systems*

AI-DRIVEN PERSONALITY INSIGHTS

RAVENSTONE
REFERENCE DECK.

Using Hierarchical Clustering

Theoretical Review

A. Automated Personality Testing

The advancement of AI and Big Data technology offers new ways to identify someone's personality through computer-based assessments. In some cases, these computer evaluations are almost or even more accurate than human assessments.

B. Big Five Inventory (BFI-10)

Introduced in the 1980s, the BFI tool measures one's tendencies towards the Big Five personality categories. The BFI questionnaire was reduced from 44 questions to 10, known as BFI-10, to accomplish the same assessment in a minute or less.

C. Unsupervised Learning

This is a method used to gather insights from data mining, generally applied to process unlabeled data.

D. Cosine Similarity

Cosine Similarity is a method used to find the similarity value between two vectors, based on the angle cosine.

E. Agglomerative Hierarchical Clustering (AHC)

This is a bottom-up hierarchical clustering method that classifies data based on the distances between clusters.

F. Silhouette Score

This is a statistical calculation method used to estimate the best number of clusters for a dataset.

$$Silhouette\ Score = SI_k = \frac{1}{n}\sum_{i=1}^{n}\frac{(b_i - a_i)}{\max(a_i, b_i)}$$

Methodology

The personality prediction model was built using Python and leveraged the scikit-learn library to apply the Agglomerative Hierarchical Clustering method.

AI-DRIVEN PERSONALITY INSIGHTS

Using Hierarchical Clustering

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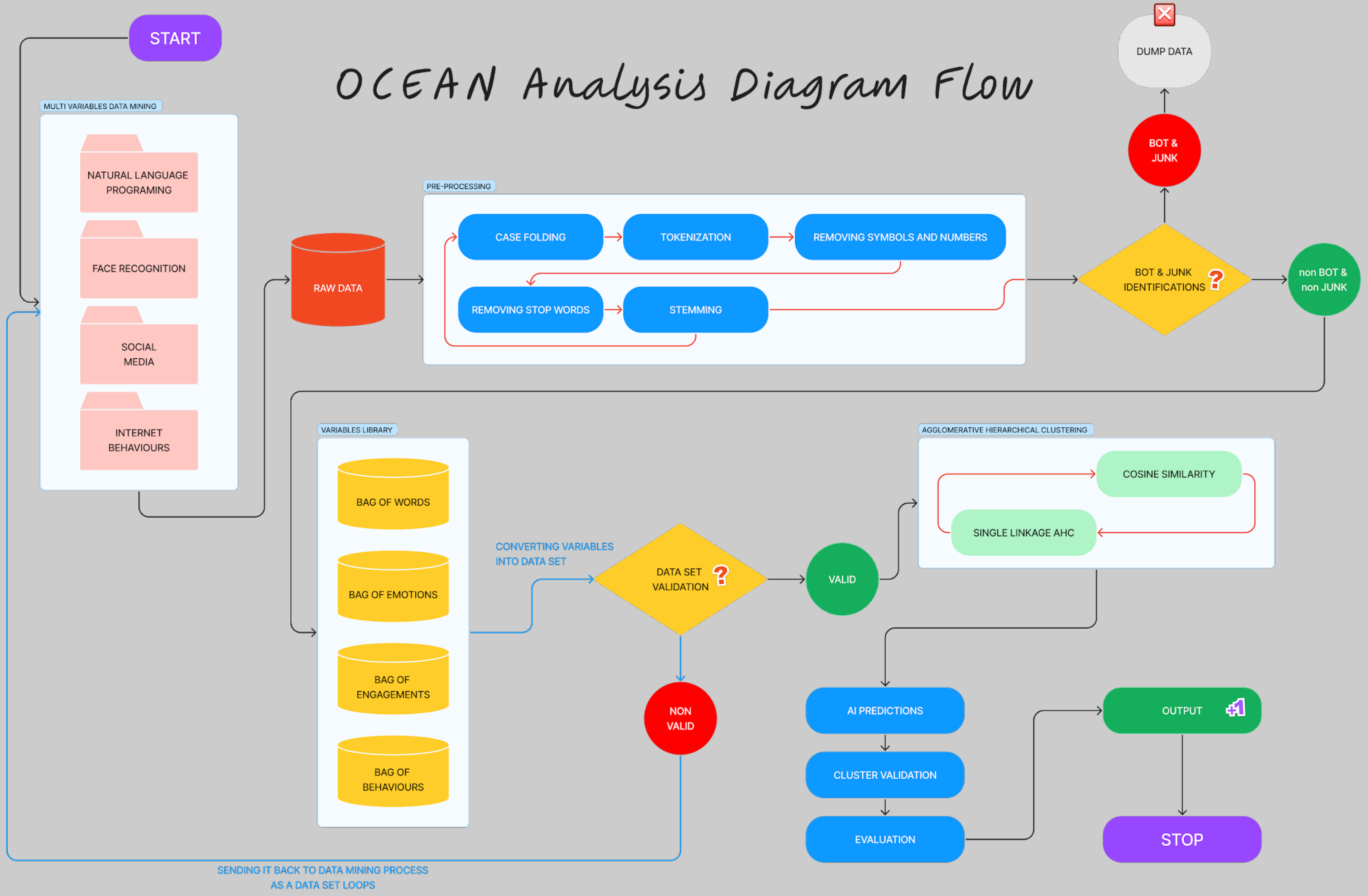

EMOTION AI: ADVANCED KNN-BASED PREDICTIVE MODELING

We employed a state-of-the-art framework for real-time human emotion detection utilizing machine learning and artificial intelligence, particularly K-Nearest Neighbors (KNN) algorithm. The system aims to revolutionize human-object interaction, enabling enhanced experiences with devices like computers and robots, as well as supporting remote psychological consultations.

A. Human Emotion

Human emotions are complex transient states that are evoked by internal or external stimuli. Unlike enduring characteristics like mood or temperament, emotions are temporary and can be accurately detected by analyzing vocal signals. Ongoing research aims to refine our voice-based emotion recognition systems.

B. Vocal Signal Characteristics

The human voice is a composite signal with frequency measured in Hertz (Hz) and amplitude quantified in decibels. It serves as a powerful conduit for communication, comprising varying vocal tract shapes, such as the laryngeal pharynx and nasal pharynx, that contribute to unique vocal signatures.

C. Vocal Types

Vocal types range from Tenor to Bass in males and Soprano to Alto in females, each having its own specific frequency range. These types are crucial in understanding the emotional state conveyed through speech.

D. K-Nearest Neighbors (KNN)

The K-NN algorithm is a supervised learning approach ideal for classifying new data points based on attribute similarity. It uses Euclidean distance as the metric for proximity measurement, and the class of the nearest neighbors is taken as the output class for the new data point.

EMOTION AI: ADVANCED KNN-BASED PREDICTIVE MODELING

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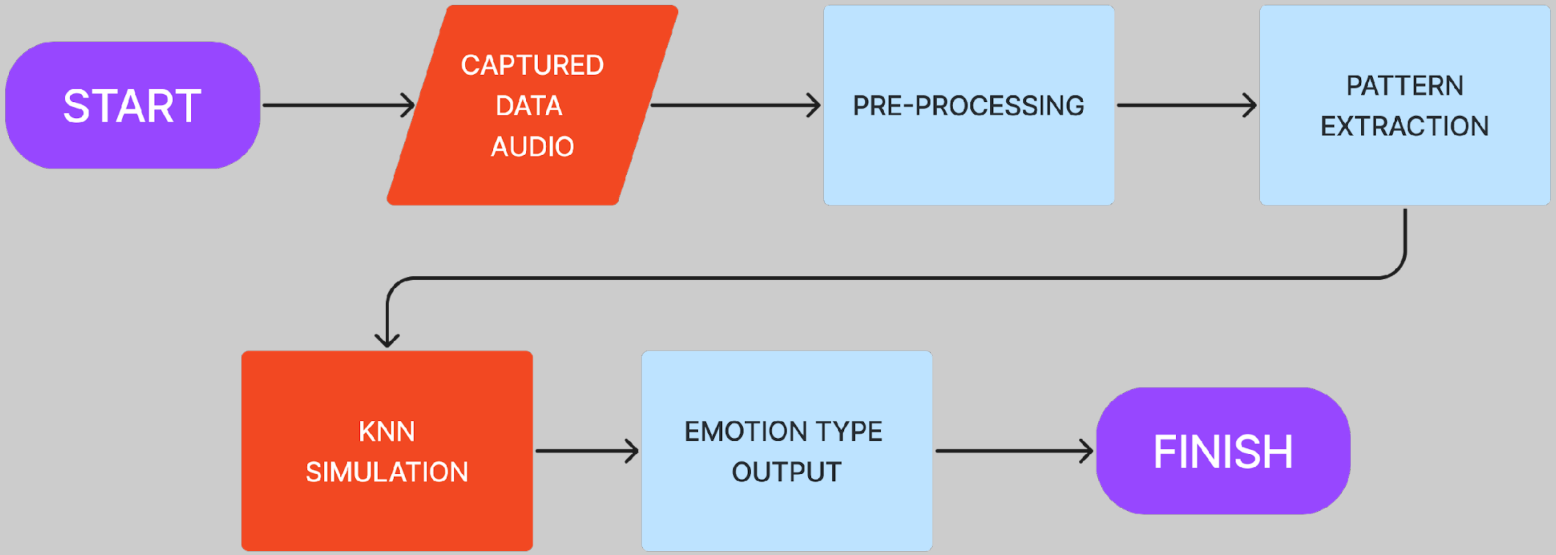

EMOTION AI: ADVANCED KNN-BASED PREDICTIVE MODELING

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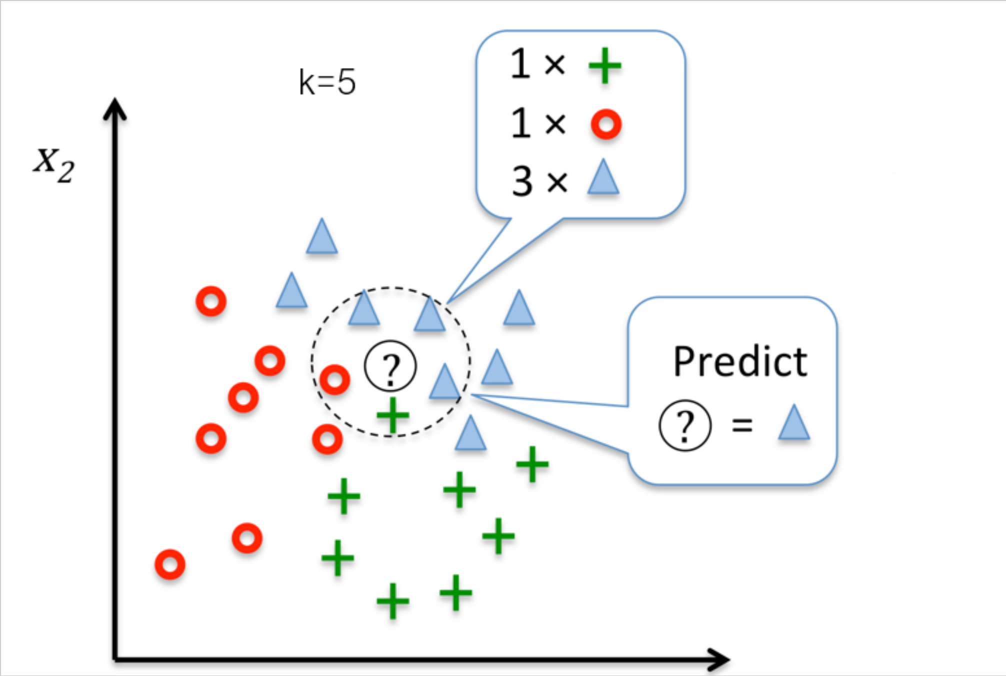

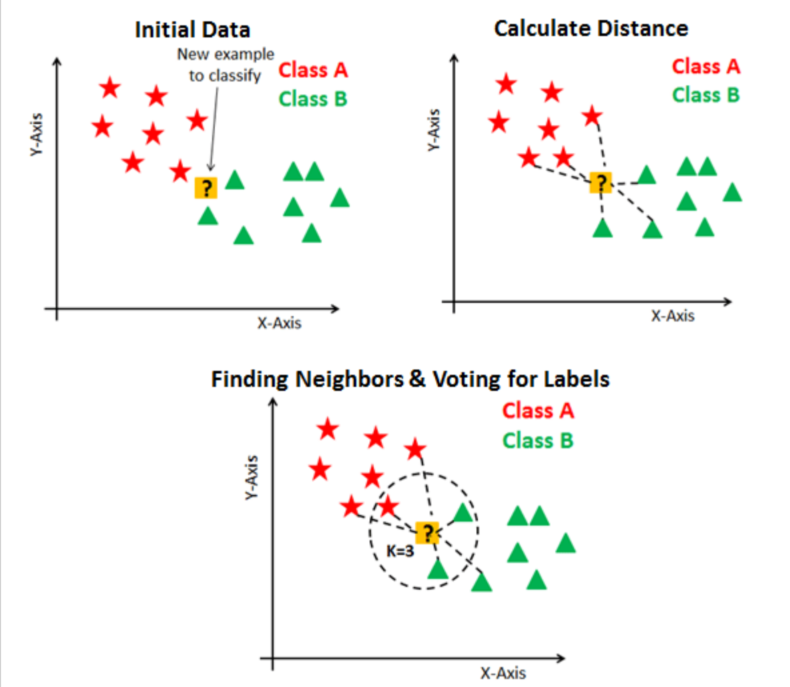

ADVANCED SENTIMENT ANALYSIS

Using Deep Learning

RAVENSTONE
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Introduction

Automated sentiment analysis is constrained by complexities within natural language processing, significantly affecting the overall accuracy in detecting emotional polarity.

Rather than solely focusing on data structures and correlations, we advocate for a shift towards lifelong learning strategies. This approach enables comprehensive data analysis, leading to better visualization and decision-making within complex network settings.

Machine Learning Models

Cutting-edge deep learning architectures such as Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN) are employed to tackle various sentiment analysis challenges, including but not limited to polarity-based and aspect-based sentiment analysis.

Deep Learning & TF-IDF

Our methodology integrates these deep learning architectures with Term Frequency-Inverse Document Frequency (TF-IDF) and word embeddings, providing a nuanced yet powerful approach to sentiment analysis.

Our Goal

Our multidisciplinary approach, we are addressing both theoretical and technical challenges, thereby establishing a new gold standard in the effectiveness of sentiment analysis.

ADVANCED SENTIMENT ANALYSIS

Using Deep Learning

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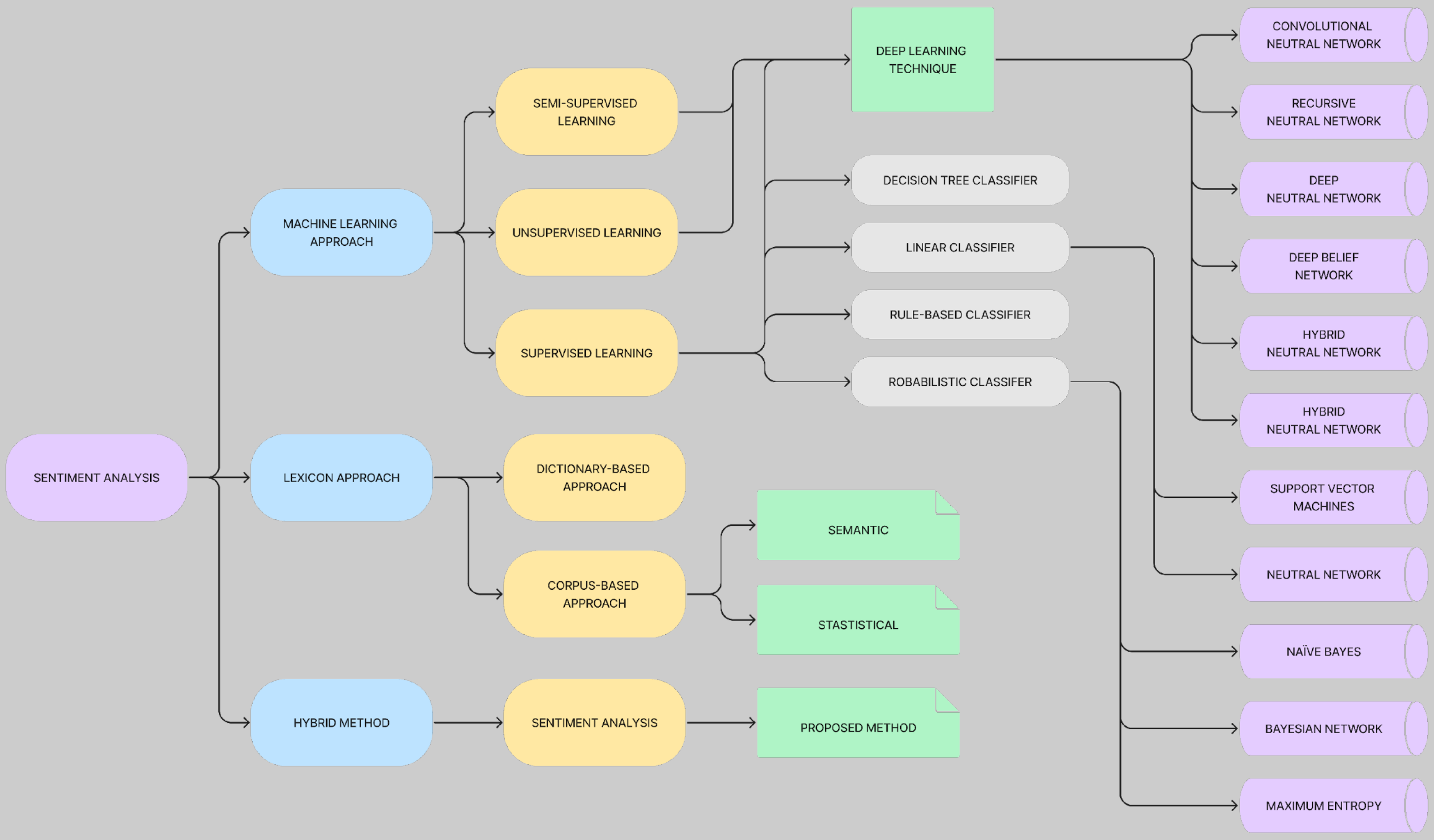

OPTIMIZED ELECTABILITY PREDICTION IN CLASSIFICATION MODELS

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Using Advanced F1 Scoring

Introduction
The F1 score serves as an instrumental metric for evaluating the performance of classification models, particularly in scenarios with imbalanced class distributions. Although customarily deployed in binary classification tasks, this metric finds applicability in multi-class scenarios by calculating the F1 score independently for each class.

Key Methodology for Electability Estimation Using F1 Score:
1.Data Preparation: Ensure the availability of a dataset comprising accurate class labels and model-generated predictions.

1. **Critical Variables**: If 'Emotion' serves as the dependent variable, crucial independent variables would include:
    1. Issue Orientation (positive and negative)
    2. Emotional Affiliation Data (ethnicity, religion, and social organizations)
    3. Party Involvement Metrics (interest in party, party sympathizers, party membership)
    4. Gender Data (male and female)
    5. Candidate Persona Metrics (credibility, capabilities, reputation/image)

2.Confusion Matrix Computation: Utilize the confusion matrix to discern the number of correct and incorrect predictions for each class. This matrix illuminates the model's classification efficacy across various categories.
3.Precision and Recall Calculation: Leverage the confusion matrix to calculate precision and recall metrics for each class. Precision is the ratio of true positives to the total number of positive predictions, while recall is the ratio of true positives to the actual number of positive instances.
4.F1 Score Calculation: Employ the derived precision and recall values to compute the F1 score using the formula (Fig1). $F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$.

The F1 score harmonizes precision and recall, yielding a value between 0 and 1—where 1 epitomizes optimal performance.

1.F1 Score Weighting: In scenarios where the dataset exhibits class imbalance, one could assign weights to the F1 scores based on the relative importance of each class in the specific context.
2.F1 Score Comparison: Benchmarking the F1 scores across diverse models delivers insights into their relative electability. Models with higher F1 scores typically exhibit superior class prediction performance.

For achieving optimal data accuracy, extensive human intervention and software development are requisite. Real-world phenomena that can be direct variables influencing someone's electability level need to be included.
Advanced Calculation Schema: The joint probability for electing a presidential and vice-presidential candidate employs conditional probability with the formula: $\boxed{P(A|B) = \frac{P(A \cap B)}{P(B)}}$

Winning Rate Prediction (WRP): It is computed using the formula:
WRP=PositiveEmotions(trust+joy+surprise)+[8%×(AverageElectability+Popularity)]

This methodology underscores the sophistication of modern classification techniques and the inherent challenges in crafting predictive models that balance both precision and recall.

ADVANCED PREDICTIVE AI

State-of-the-Art Sentiment Analysis

Leveraging powerful machine learning techniques based on Neural Networks, we've created a state-of-the-art sentiment analysis framework that categorizes data acquired from social media platforms and online articles.

Semantic Data Grouping

Utilizing sophisticated Machine Learning approaches such as "Word Embedding" and "Topic Modeling," we're capable of discerning and grouping data into semantically coherent containers.

Real-Time NLP Engine

Our NLP engine employs a similar methodology to "listen" to discourses across various platforms that share semantic proximity, once again using "Word Embedding" and "Topic Modeling" techniques. The aggregated data is then visualized based on the number of engaged devices or 'audiences.'

Integrated Sentiment Clustering

The collected data is categorized into sentiment clusters: POSITIVE, NEUTRAL, and NEGATIVE. This categorization uses advanced sentiment analysis combined with Face Recognition technology to detect micro-expressions and Voice Recognition technology to gauge emotional tone

Emotional Stratification

Our uniquely integrated sentiment analysis system combines advanced Face Recognition technologies capable of detecting micro-expressions and Voice Recognition technologies.

K-NN Algorithm in Sentiment Analysis

Our machine learning model classifies these tones into various emotional states: Trust, Joy, Surprise, Anticipation, Sadness, Fear, Anger, and Disgust using the K-NN (K-Nearest Neighbour) methodology..

ADVANCED PREDICTIVE AI

Computational Modeling Approaches: Auditory, Visual, and Social Media Data*

1.For auditory data, we employ NLP models built on Neural Networks, using a supervised modeling approach.
2.For visual data, OpenCV library is utilized as a training dataset for recognizing specific micro-expressions.
3.Additional supporting data is harvested from social media using keyword-based tone identification, e.g., Positive tone is represented by keywords like Happy, Joyful, Grateful, etc.

Audience Emotional Profile: Proportional Visualization of Aggregate Data

This information is aggregated into respective emotional containers, visualized as proportional audience engagement metrics

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