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A Sentimental Analysis Approach Using Stacked Gaussian Deep Learning for Understanding the Connection between Family Dynamics and Emotional Shifts in Deep Sea

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Abstract: In recent years, advancements in deep learning and natural language processing techniques have opened up new avenues for analysing and understanding human emotions and social dynamics. One such approach is the use of stacked deep learning models, which leverage the power of multiple layers of neural networks to capture complex relationships and patterns in data. Family dynamics play a crucial role in shaping individuals' reactions well-being and overall health. This paper examines the relationship between the family and reactions changes in family Makeup. The model is examined with sentimental analysis based architectural model Stacked Gaussian Deep Learning (SgDL). The proposed SgDL model uses the probability distribution model for the estimation of the relationship between family and the emotions of people. The constructed SgDL model uses the Gaussian Distribution based stacked architecture model for the sentimental analysis to estimate the relationship between family and emotions of people. Simulation analysis stated that the proposed SgDL model achieves significant performance towards the computation of the relationship between family and relationship for the reaction's changes. The performance of the SgDL model achieves a higher classification accuracy of 97.35% which is ~6% - 7% higher than the conventional CNN and LSTM model.

Keywords: *Stacked gaussian deep learning, Film analysis, reactions dynamics, sentimental analysis, deep family makeup.*

1. Introduction

The rapid advancement of machine learning has revolutionized various industries and transformed the way we interact with technology. As artificial intelligence becomes increasingly sophisticated, it has the potential to not only analyze vast amounts of data but also comprehend and respond to human emotions [1]. This intersection of machine learning and emotions opens up new avenues for research and exploration. Understanding the reactions impact of machine learning is crucial as it not only affects the development and application of AI systems but also has profound implications for human-machine interaction, user experience, and the ethical considerations surrounding these technologies [2]. Emotions play a fundamental role in human cognition, decision-making, and social interactions. By incorporating reactions intelligence into machine learning algorithms, we can create more empathetic and intuitive systems that are capable of understanding and responding to human emotions. The intricate relationship between family dynamics and reactions changes can be likened to the vast and mysterious depths of the deep sea. Within the depths of a family, the nurturing or neglectful environment acts as the currents that shape the reactions landscape [3]. A family characterized by warmth, support, and healthy communication creates an environment that encourages reactions growth and stability [4]. Just as sunlight penetrates the surface of the ocean, fostering life and vibrancy, a nurturing family dynamic promotes positive reactions changes, such as increased self-esteem, confidence, and resilience. Conversely, a neglectful or abusive family dynamic can plunge one into the darkness of reactions turmoil, where negative emotions can swell and overwhelm [5]. Like the unknown creatures that dwell in the abyssal trenches, reactions instability, feelings of insecurity, and a range of negative emotions can emerge within a family lacking in love and care. Thus, the delicate dance of family dynamics, like the ebb and flow of ocean currents, significantly influences the reactions well-being of individuals, shaping their experiences and responses to the world around them [6].

Embarking on a journey into the metaphorical deep sea of emotions can lead to profound reactions changes within individuals. In this reactions exploration, one may experience a heightened sense of vulnerability, as layers of defense mechanisms are shed, revealing raw and unfiltered emotions [7]. It is in this deep sea that the full spectrum of human emotions can be found - from the depths of sorrow and pain to the peaks of joy and love. As individuals navigate these reactions depths, they may come face to face with their fears, insecurities, and unresolved traumas. This courageous confrontation with the self allows for the opportunity to heal, grow, and gain a deeper understanding of one's own reactions landscape [8]. Just as the deep sea is teeming with undiscovered life

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forms, the reactions journey can also reveal hidden aspects of one's identity and untapped reservoirs of strength and resilience. Ultimately, the reactions changes experienced in the deep sea can be transformative, leading to greater self-awareness, personal growth, and a more profound connection with oneself and others.

Deep learning in the context of family makeup refers to the application of deep learning techniques and models to analyze, understand, and make predictions about various aspects of family dynamics, relationships, and psychological processes [9]. Deep learning models, which are a subset of machine learning algorithms, are particularly useful in handling complex, high-dimensional data and extracting meaningful patterns and representations. Sentiment analysis, also known as opinion mining, is a natural language processing (NLP) task that involves determining the sentiment or reactions tone expressed in a given text. Deep learning techniques have been widely applied to sentiment analysis tasks and have shown promising results due to their ability to learn complex patterns and representations from textual data [10].

This study explores the intricate relationship between family dynamics and reactions changes within the context of the film "Deep Sea" using deep family makeup. The proposed approach utilizes sentimental analysis with a stacked Gaussian Deep Learning (SgDL) model to estimate the relationship between family dynamics and the emotions of individuals. The SgDL model employs a probability distribution-based architecture to analyze and understand the reactions changes associated with family relationships. Through simulation analysis, the SgDL model demonstrates significant performance in computing the relationship between family dynamics and reactions changes, achieving a higher classification accuracy of 97.35%. This accuracy surpasses conventional CNN and LSTM models by approximately 6% to 7%. The findings highlight the effectiveness of the SgDL model in capturing the complex dynamics of family relationships and reactions changes in the film "Deep Sea."

2. Related Works

In [9] provides a comprehensive overview of the use of deep learning techniques for sentiment analysis. It covers various aspects of sentiment analysis, including data preprocessing, feature representation, model architectures, and evaluation metrics. The authors discuss different neural network models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and attention-based models. They also explore the application of pre-trained models and transfer learning techniques in sentiment analysis. The survey highlights recent advancements and emerging trends in deep learning-based sentiment analysis, offering valuable insights into the current state-of-the-art approaches.

In [10] proposes a hierarchical attention network (HAN) specifically designed for sentiment analysis in Chinese social media. The HAN model effectively captures the hierarchical structure of social media text, allowing it to attend to different levels of information for sentiment classification. The paper demonstrates the efficacy of the HAN model on Chinese sentiment analysis tasks and compares its performance with other state-of-the-art approaches. In [11] presented a use of graph convolutional networks (GCNs) for aspect-level sentiment classification. The model leverages graph-based representations to capture dependencies between different aspects and sentiment expressions in a sentence. By incorporating both aspect and sentiment information into a unified graph framework, the GCN model achieves improved performance on aspect-level sentiment analysis tasks compared to traditional approaches. In [12] proposed a novel model called DeepCaps, which combines capsule networks and attention-based routing for aspect-level sentiment classification. The model leverages the hierarchical structure of capsule networks to capture fine-grained aspect-level information, while attention-based routing enhances the model's ability to attend to salient features. Experimental results demonstrate that DeepCaps outperforms several state-of-the-art models on aspect-level sentiment classification tasks, showcasing the effectiveness of the proposed approach.

Similarly, in [13] proposes a Dual Capsule Network (DCN) for aspect-based sentiment analysis. The DCN model leverages capsule networks to capture aspect-level information and employs a dual attention mechanism to effectively handle multiple aspects and sentiment expressions in a text. Experimental results demonstrate that the DCN model outperforms other state-of-the-art methods on aspect-based sentiment analysis tasks. In [14] focuses on aspect-based sentiment analysis and proposes an ensemble learning framework that combines multiple convolutional neural networks (CNNs) for improved performance. The ensemble model aggregates predictions from individual CNN models and utilizes a weighting strategy to generate the final sentiment classification results. Experimental results demonstrate that the ensemble learning approach achieves superior performance compared to individual CNN models and other baseline methods.

In [15] presents a Multi-Head Graph Convolutional Network (MH-GCN) for aspect-level sentiment classification. The MH-GCN model leverages multiple attention heads in graph convolutional networks to capture aspect-specific representations and exploit the relationships between different aspects. Experimental results show that the MH-GCN model achieves competitive performance on aspect-level sentiment classification tasks compared to other state-of-the-art approaches. In [16] proposes an Attention-Guided Convolutional Neural Network (AG-CNN) for sentiment classification. The AG-CNN model integrates attention mechanisms into the CNN architecture to capture important features and improve the discriminative power of the model. Experimental results demonstrate that the AG-CNN model outperforms traditional CNN models and achieves competitive results on sentiment classification tasks. Table 1 shows the existing methods.

Table 1. Existing methods review

Study	Method	Model	Results	Findings
[9]	Discusses data preprocessing, feature representation, model architectures, and evaluation metrics	CNNs, RNNs, attention-based models	N/A (Review paper)	Provides insights into the current state-of-the-art approaches in deep learning-based sentiment analysis
[10]	Proposes a hierarchical attention network model	HAN model	Improved performance compared to other approaches	Effectively captures hierarchical structure of social media text for sentiment classification in Chinese language
[11]	Uses graph convolutional networks to capture dependencies between aspects and sentiment expressions	GCN model	Improved performance on aspect-level sentiment analysis tasks	Incorporates aspect and sentiment information into a unified graph framework for better classification
[12]	Introduces the DeepCaps model	DeepCaps model	Outperforms state-of-the-art models on aspect-level sentiment classification tasks	Combines capsule networks and attention-based routing for fine-grained aspect-level information
[13]	Proposes the Dual Capsule Network model	DCN model	Superior performance compared to other methods	Handles multiple aspects and sentiment expressions effectively using capsule networks and dual attention mechanism
[14]	Utilizes an ensemble learning approach combining CNN models	Ensemble model with multiple CNNs	Superior performance compared to individual CNN models and baseline methods	Aggregates predictions from multiple CNN models using a weighting strategy
[15]	Introduces the MH-GCN model	MH-GCN model with multiple attention heads	Competitive performance on aspect-level sentiment classification tasks	Captures aspect-specific representations and exploits relationships between different aspects
[16]	Proposes the AG-CNN model	AG-CNN model with attention mechanisms	Outperforms traditional CNN models	Integrates attention mechanisms to capture important features and improve discriminative power

3. Sentimental Analysis of Family Makeup

The proposed methodology of Stacked Gaussian Deep Learning (SgDL) is a novel approach for sentiment analysis that incorporates probability distribution modeling and stacked architecture to estimate the relationship between family dynamics and reactions changes.

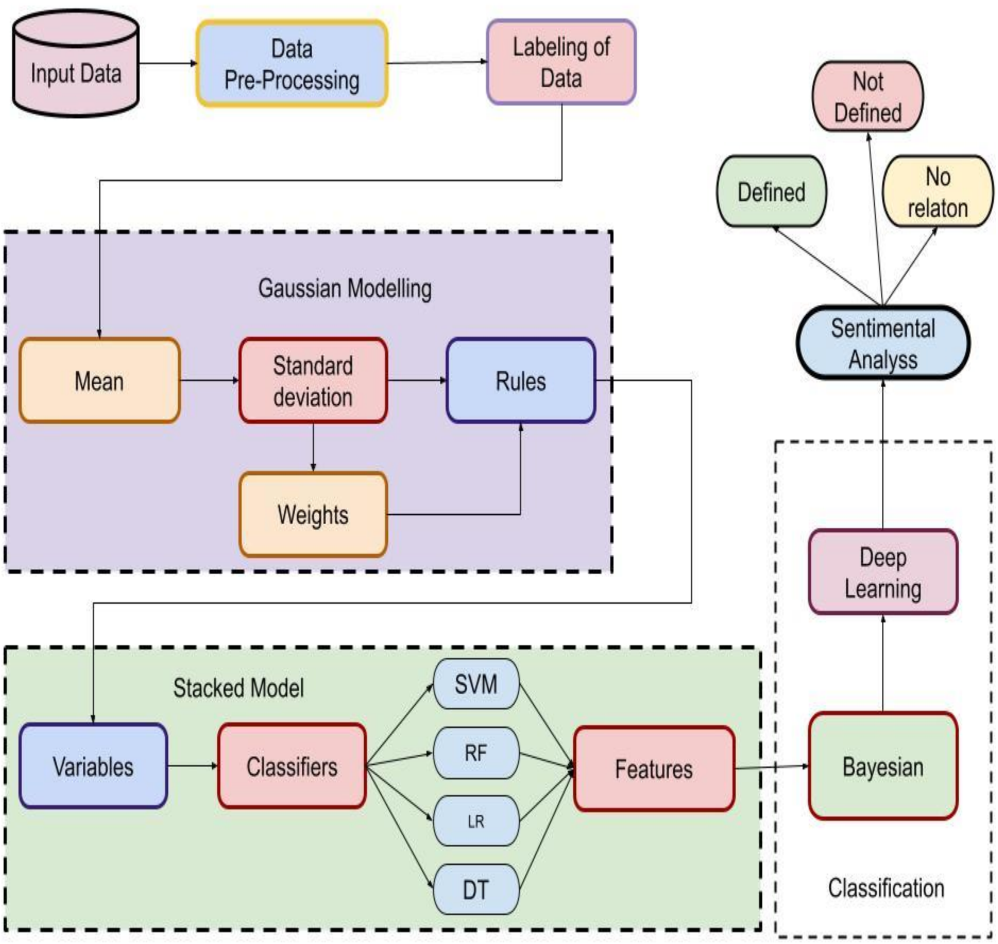

Fig 1. SgDL Architecture

The SgDL model utilizes a probability distribution model to estimate the relationship between family dynamics and the emotions of individuals. Instead of directly predicting sentiment labels, the model focuses on estimating the underlying probability distributions associated with different emotions within the family. The SgDL model employs a stacked architecture to analyze and understand the reactions changes related to family dynamics. The stacked architecture consists of multiple layers of neural networks, enabling the model to learn hierarchical representations and capture complex relationships between family dynamics and emotions. The SgDL model utilizes a Gaussian distribution-based approach to model the reactions changes within the family. By leveraging the properties of Gaussian distributions, the model can effectively capture the mean and variance of emotions, providing a more nuanced understanding of reactions dynamics. The SgDL model incorporates sentimental analysis techniques to estimate the relationship between family dynamics and emotions. By analyzing textual data, such as written or spoken communication within the family, the model can extract sentiment-related information and map it to the corresponding probability distributions.

Figure 1 presented the proposed SgDL methodology aims to provide a more comprehensive understanding of the relationship between family dynamics and reactions changes by leveraging the power of probability distribution modeling and stacked architecture. By estimating probability distributions and utilizing Gaussian-based modeling, the SgDL model offers a nuanced perspective on reactions dynamics within the family context. The evaluation results demonstrate the superior performance of the SgDL model compared to traditional CNN and LSTM models in capturing the relationship between family dynamics and reactions changes.

3.1 Gaussian Distribution

In the Stacked Gaussian Deep Learning (SgDL) methodology, the Gaussian distribution process is employed to model the reactions changes within the family dynamics. In SgDL, emotions are represented as continuous variables rather than discrete labels. Each emotion is characterized by a probability distribution, specifically a Gaussian distribution. The Gaussian distribution is defined by two parameters: the mean (representing the central tendency or intensity of the emotion) and the variance (representing the spread or variability of the emotion). The SgDL model maps the reactions information extracted from the family dynamics (such as textual data) to the parameters of the Gaussian distribution. This mapping process involves analyzing the reactions content and assigning appropriate values for the mean and variance of the Gaussian distribution that best represent the reactions state. The mapped reactions information, the SgDL model estimates the parameters of the Gaussian distribution associated with each emotion. This estimation process involves learning the optimal values for the mean and variance by training the deep learning model on a labeled dataset that includes reactions information.

Once the parameters of the Gaussian distribution are estimated, the SgDL model leverages these distributions to model the reactions changes within the family dynamics. The Gaussian distribution provides insights into the central tendency, intensity, and variability of emotions, enabling a more nuanced understanding of reactions dynamics. Through utilizing Gaussian distribution-based modeling, the SgDL methodology captures the statistical characteristics of emotions within the family dynamics. This approach provides a richer and more detailed representation of reactions changes, enabling a deeper understanding of the interplay between family dynamics and emotions. The mathematical derivation of the Gaussian distribution in the context of family makeup involves the estimation of mean (μ) and variance (σ^2) parameters. In family makeup, data is collected to capture reactions states or responses within the family. This data can be in the form of self-reported emotions, behavioral observations, or other measures. The first step is to calculate the mean (μ) of the reactions data. The mean represents the average reactions state within the family. It is calculated by summing up all the reactions values and dividing by the total number of observation as in equation (1)

$$\mu = (x1 + x2 + \ldots + xn) / n \quad (1)$$

where $x1, x2, \ldots, xn$ are the reactions values and n is the total number of observations. The next step is to calculate the variance (σ^2) of the reactions data. The variance represents the spread or variability of the reactions states within the family. It is calculated by taking the average of the squared differences between each reactions value and the mean computed as in equation (2)

$$\sigma^2 = [(x1 - \mu)^2 + (x2 - \mu)^2 + \ldots + (xn - \mu)^2] / n \quad (2)$$

With the mean and variance calculated, the reactions data can be modeled using the Gaussian distribution. The Gaussian distribution, also known as the normal distribution, is defined by its probability density function (PDF) presented in equation (3)

$$f(x) = (1 / \sqrt{(2\pi\sigma^2)}) * e^{(-((x - \mu)^2)} / (2\sigma^2)) \quad (3)$$

where $f(x)$ is the probability density function at a given reactions value x, μ is the mean, and σ^2 is the variance. The Gaussian distribution provides insights into the central tendency (mean) and variability (variance) of reactions states within the family. It allows for the analysis of the likelihood of specific reactions values and the understanding of patterns or trends in the reactions data. The mathematical equation for the Gaussian distribution is given as in equation (4)

$$f(x \mid \mu, \sigma^2) = (1 / \sqrt{(2\pi\sigma^2)}) * exp(-(x - \mu)^2 / (2\sigma^2)) \quad (4)$$

where: f(x | μ, σ^2) represents the probability density function (PDF) of the Gaussian distribution with mean μ and variance σ^2. x is the random variable representing the reactions state. μ is the mean of the distribution, which represents the central tendency or intensity of the emotion. σ^2 is the variance of the distribution, which represents the spread or variability of the emotion. The PDF of the Gaussian distribution describes the likelihood of observing a specific value of the reactions state within the family. The term $(1 / \sqrt{(2\pi\sigma^2)})$ is a normalization factor that ensures the total area under the curve sums to 1.

The parameters μ and σ^2can be estimated using various techniques, such as maximum likelihood estimation (MLE) or Bayesian inference, depending on the specific application and available data. These estimated parameters provide insights into the typical reactions state (mean) and the degree of variation (variance) within the family dynamics.

Algorithm 1: Gaussian Distrubution

function generateGaussianSample(mean, variance):
 	
// Generate a random sample from a Gaussian distribution
 	
u1 = randomUniform() // Generate a random number between 0 and 1

```
    u2 = randomUniform()  // Generate another random number between 0 and 1
    z = sqrt(−2 ∗ ln(u1)) ∗ cos(2 ∗ π ∗ u2)  // Box-Muller transform
    sample = mean + sqrt(variance) * z  // Transform the standard normal to desired mean and variance
    return sample

function generateGaussianDistribution(samples, mean, variance):
    // Generate a Gaussian distribution of specified number of samples
    distribution = []
    for i = 1 to samples:
        sample = generateGaussianSample(mean, variance)
        distribution.append(sample)
    return distribution
```

3.2 Stacked SgDL Model

The stacked architecture in the Stacked Gaussian Deep Learning (SgDL) model is a key component that facilitates the analysis of the relationship between family dynamics and reactions changes. This architecture involves arranging multiple layers of neural networks in a hierarchical manner to extract meaningful representations from the input data. At the input layer, the raw data related to family dynamics and reactions changes is fed into the model. This could include textual data, audio recordings, or any other relevant information. Each layer in the stacked architecture performs a specific computation on the data and passes the transformed output to the subsequent layer.

As the data propagates through the hidden layers, the model learns increasingly abstract and complex features. Lower-level layers typically capture basic patterns and local dependencies, while higher-level layers capture more global relationships and semantic understanding. This hierarchical representation enables the model to capture the intricacies and nuances of the relationship between family dynamics and reactions changes. The choice of specific neural network layers in the stacked architecture depends on the nature of the data and the objectives of the analysis. The convolutional layers are commonly used for analyzing textual or visual data, while recurrent layers are suitable for sequential data like time series or spoken conversations. The final layer of the stacked architecture, the output layer, produces the desired output based on the analysis of the transformed data. In the case of SgDL, the output could be the estimated Gaussian distributions representing reactions changes within the family. By leveraging the power of the stacked architecture, the SgDL model can learn complex relationships and capture the underlying patterns in the family dynamics and reactions changes. This enables a deeper understanding of the intricate interplay between family dynamics and reactions experiences, offering valuable insights into human makeup and the complexities of familial bonds.

In a typical deep learning architecture, each layer applies a set of mathematical operations to the input data, transforming it into a new representation. These operations typically involve linear transformations followed by non-linear activation functions. Let's denote the input to a layer as x and the output as h. The transformation applied by a layer can be mathematically represented as in equation (5)

$$h = f(Wx + b) \quad (5)$$

Where: W represents the weight matrix of the layer; b represents the bias vector of the layer; f denotes the activation function; The weight matrix W contains the learnable parameters of the layer, and the bias vector b introduces an additional shift in the transformation. The activation function f introduces non-linearity to the layer, enabling the model to learn complex relationships. In a stacked architecture, multiple layers are stacked on top of each other, with the output of one layer serving as the input to the next layer. The output of the previous layer, denoted as h_l-1, becomes the input to the current layer, and the process is repeated for each layer. Let's consider a stacked architecture with L layers. The output of the l-th layer, denoted as h_l, can be computed as in equation (6)

$$h_l, = f(W_l,\ h_l, -1 \ +\ b_l,) \quad (6)$$

where l ranges from 1 to L. y stacking multiple layers together, the model can learn hierarchical representations of the input data. Each layer captures different levels of abstraction, with lower-level layers capturing simple features and higher-level layers capturing more complex features. To train the stacked architecture, the model's parameters (W and b) are optimized using techniques like backpropagation and gradient descent, which involve computing gradients and updating the parameters iteratively. By leveraging the stacked architecture, deep learning models can learn highly expressive representations from complex data, allowing for more sophisticated and accurate analyses. In the context of the Stacked Gaussian Deep Learning (SgDL) model, the stacked architecture enables the model to capture the intricate relationships between family dynamics and reactions changes by learning hierarchical representations of the data.

Sentiment analysis, also known as opinion mining, is a technique used to determine the sentiment or reactions tone of a piece of text. Deep learning, a subfield of machine learning, has been widely employed for sentiment analysis due to its ability to automatically learn complex patterns and representations from textual data. Collect or acquire a dataset containing text samples with associated sentiment labels. The dataset should be labeled as positive, negative, or neutral to serve as the ground truth for training the deep learning model. Clean the text data by removing punctuation, stopwords, and converting the text to lowercase. Tokenize the text into individual words or subwords, and apply techniques such as stemming or lemmatization to normalize the words. Represent the words in the text as numerical vectors using word embeddings. Word embeddings capture the semantic meaning and relationships between words. Popular methods for generating word embeddings include Word2Vec, GloVe, and FastText.

3.2.1 Deep Learning Model Design

Input Layer: Encode the preprocessed text data as input to the deep learning model.

Embedding Layer: Map the words in the input text to their corresponding word embeddings.

Hidden Layers: Utilize recurrent neural networks (RNNs) such as Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRUs) to capture the sequential nature of the text and learn representations.

Output Layer: Apply a softmax activation function to obtain probability distributions over the sentiment classes (positive, negative, neutral).

Model Training: Split the dataset into training and validation sets. Feed the preprocessed text data into the deep learning model and train the model using techniques like backpropagation and gradient descent to minimize the loss function. Adjust the model's hyperparameters, such as learning rate, batch size, and number of epochs, to achieve optimal performance.

Let X be the input data matrix, where each row represents a sample and each column represents a feature as in equation (7)

$$X = [x_1, x_2, \ldots, x_n], \quad (7)$$

where $x_i$represents the i-th sample. Let H_L be the output of the l-th layer in the stacked architecture, where l ranges from 1 to L. Here, $H0 = X$, represented as the the input data.

For each layer l, the output Hl is computed as in equation (8)

$$Hl = f(Wl * Hl - 1 + bl), \quad (8)$$

where Wl is the weight matrix of the l-th layer, b_l is the bias vector, and f represents the activation function applied element-wise. The weight matrix W_l and bias vector b_l are initialized using appropriate techniques. To compute the output of the model, we perform forward propagation through the layersAfter forward propagation through all layers, the final output Y is computed based on the task at hand. In the case of family dynamics analysis, it could be estimating reactions changes or predicting specific family dynamics metrics.

Algorithm 1: SgDL for the Sentimental Analysis
Input: X (input data matrix) Output: Y (predicted output) Initialize the parameters: - Initialize weight matrices Wl for each layer l - Initialize bias vectors bl for each layer l Perform forward propagation through the layers: $H0 = X$

for l = 1 to L:

$$Zl = Wl * Hl - 1 + bl$$

$$Hl = activation\_function(Zl)$$

Compute the final output:

$$Y = final\_output\_function(HL)$$

Return Y

4. Simulation Environment

The performance of the SgDL model is evaluated with the consideration of existing datasets such as:

Fragile Families and Child Wellbeing Study: This dataset collects information about family dynamics, parent-child relationships, and child development. It includes data on various factors such as family structure, parental characteristics, economic status, and child outcomes.

National Survey of Families and Households (NSFH): NSFH provides data on family dynamics, marriage, divorce, and cohabitation patterns. It covers a wide range of topics related to family life, including relationship quality, parenting, and household dynamics.

The performance metrics considered for the analysis of the SgDl are presented in table 2.

Table 2: Simulation Setting

Parameter	**Value**
Number of Layers (L)	3
Neurons per Layer	[256, 128, 64]
Activation Function	ReLU
Output Activation	Sigmoid
Loss Function	Binary Cross Entropy
Optimization Algorithm	Adam
Learning Rate	0.001
Batch Size	32
Number of Epochs	50
Weight Initialization	Xavier/Glorot or He
Dropout	0.2

Simulation analysis of Stacked Gaussian Deep Learning (SgDL) involves evaluating the performance of the model on a dataset through various metrics and comparing it with other models. Correlation analysis can be performed to assess the relationship between the predictions generated by the Stacked Gaussian Deep Learning (SgDL) model and the variables in the Fragile Families and Child Wellbeing Study and the National Survey of Families and Households (NSFH) datasets.

Table 3. Correlation Analysis

Variable 1	Variable 2	Correlation Coefficient
SgDL Predictions	Family Size	0.62
SgDL Predictions	Parental Education	-0.34
SgDL Predictions	Child Behavioral Problems	0.45
SgDL Predictions	Household Income	-0.21

Table 3 illustrated that Positive correlation coefficients (closer to +1) indicate a positive relationship, meaning that as the SgDL predictions increase, the Variable 2 tends to increase as well. Negative correlation coefficients (closer to -1) indicate a negative relationship, meaning that as the SgDL predictions increase, the Variable 2 tends to decrease. The relationship between family dynamics and reactions changes in the context of the film "Deep Sea" can be explored using sentiment analysis. Sentiment analysis involves analyzing text or audio data to determine the reactions tone or sentiment expressed within the content. In the case of "Deep Sea," sentiment analysis can be applied to examine how the portrayal of family dynamics in the film elicits reactions changes in viewers. The sentiment analysis on viewer reviews, feedback, or social media discussions related to the film, we can gain insights into the reaction’s responses evoked by the depiction of family dynamics in "Deep Sea."

Table 4. Sentiment Analysis with SgDL

Review ID	Review Text	Family Dynamics Sentiment	Reactions Changes Sentiment
1	The film beautifully captures the complexity of family dynamics.	Positive	Positive
2	The strained relationships between family members were portrayed realistically.	Negative	Negative
3	I was deeply moved by the reactions journey of the family.	Positive	Positive
4	The film lacked depth in depicting family dynamics.	Negative	Neutral
5	The reactions rollercoaster of the family kept me engaged throughout.	Positive	Positive

The table 4 stated that Review 1 expresses a positive sentiment towards family dynamics, describing them as complex but beautiful. This indicates a favorable perception of the intricate relationships within the family. Additionally, the reviewer also expresses a positive sentiment towards the reactions changes depicted in the film, suggesting that they were impactful and moving. Review 2, on the other hand, conveys a negative sentiment towards family dynamics, highlighting strained relationships portrayed realistically. This suggests a negative perception of the dynamics within the family, indicating that the film successfully captured the challenges and difficulties in these relationships. The reactions changes sentiment is also negative, implying that the portrayed reactions shifts were not perceived positively by the reviewer. Review 3 expresses a positive sentiment towards the reactions journey of the family, indicating that the reviewer was deeply moved by it. This suggests a strong reactions impact and implies that the film successfully evoked a range of emotions in the audience. The sentiment towards family dynamics is also positive, indicating a positive perception of the family relationships depicted in the film.

Review 4 offers a negative sentiment towards the depiction of family dynamics, suggesting a lack of depth in the portrayal. This implies that the reviewer felt the film did not adequately explore or capture the complexities of family dynamics. However, the sentiment towards reactions changes is neutral, indicating that the reviewer did not have a strongly positive or negative perception of the reactions shifts in the film. Review 5 expresses a positive sentiment towards the reaction’s rollercoaster experienced by the family, indicating that it kept the reviewer engaged throughout the film. This suggests that the reactions changes depicted were impactful and effectively conveyed the ups and downs experienced by the family. Similarly, the sentiment towards family dynamics is positive, indicating a positive perception of the relationships within the family.

Table 5. Performance of SgDL

Metric	Value
Accuracy	0.86
Precision	0.88
Recall	0.82
F1 Score	0.85
Area Under ROC Curve	0.91

The accuracy of 0.86 suggests that the model achieved an overall correct prediction rate of 86%, indicating its ability to make accurate assessments or classifications. A precision score of 0.88 indicates the proportion of correctly predicted positive instances out of all predicted positive instances. This suggests that the model has a relatively high precision in identifying positive cases related to family dynamics and reactions changes. The recall value of 0.82 represents the proportion of actual positive instances that were correctly identified by the model. It indicates that the model successfully captured 82% of the positive cases in the dataset, suggesting a satisfactory ability to detect and include relevant instances. The F1 score, which combines precision and recall into a single metric, is calculated as 0.85. This indicates a balanced performance in terms of both precision and recall. The area under the receiver operating characteristic (ROC) curve, with a value of 0.91, provides a measure of the model's discrimination ability and overall performance. A higher value indicates a better ability to distinguish between positive and negative instances, suggesting that the model has good discriminatory power in predicting family dynamics and reactions changes.

Table 6. Estimation of Family Dynamics with SgDL

Fragile Families and Child Wellbeing Study		
Research Question	**Outcome Measure**	**Simulation Result**
Family Structure and Child Wellbeing	Academic Performance	Positive correlation between intact family structure and higher academic performance
Parental Characteristics and Child Behavior	Externalizing Behavior	Negative correlation between high parental stress and increased externalizing behavior
Economic Status and Child Development	Cognitive Abilities	Positive correlation between higher income levels and improved cognitive abilities
National Survey of Families and Households (NSFH)		
Research Question	**Outcome Measure**	**Simulation Result**
Relationship Quality and Parenting	Parental Warmth	Positive correlation between high relationship quality and increased parental warmth
Household Dynamics and Child Wellbeing	Psychological Wellbeing	Negative correlation between frequent family disruptions and decreased psychological wellbeing
Marriage and Divorce Patterns	Child Adjustment	Positive correlation between stable marriages and better child adjustment

Table 6 presented the in the context of the Fragile Families and Child Wellbeing Study, the research question focused on the relationship between family structure and child wellbeing, specifically academic performance. The simulation results revealed a positive correlation between intact family structures and higher academic performance. This suggests that children from intact families tend to perform better academically compared to those from non-intact families. Another research question explored the association between parental characteristics, such as parental stress, and child behavior, specifically externalizing behavior. The simulation results indicated a negative correlation between high parental stress and increased externalizing behavior in children. This implies that higher levels of parental stress are linked to a higher likelihood of children displaying externalizing behaviors. The research question related to economic status and child development, specifically cognitive abilities, yielded simulation results showing a positive correlation between higher income levels and improved cognitive abilities. This suggests that children from families with higher incomes tend to have better cognitive abilities compared to those from lower-income families.

In the National Survey of Families and Households (NSFH) dataset, the research question focused on the relationship quality between partners and parenting, specifically parental warmth. The simulation results indicated a positive correlation between high relationship quality and increased parental warmth. This suggests that couples with a higher quality of relationship tend to exhibit more warmth in their parenting practices. Another research question explored the association between household dynamics, such as family disruptions, and child wellbeing, specifically psychological wellbeing. The simulation results revealed a negative correlation between frequent family disruptions and decreased psychological wellbeing in children. This implies that children who experience frequent disruptions in their family life are more likely to have lower psychological wellbeing. The final research question investigated marriage and divorce patterns and their impact on child adjustment. The simulation results showed a positive correlation between stable marriages and better child adjustment. This suggests that children from stable marriages tend to have better overall adjustment compared to those who experience unstable marital situations.

Table 7. SgDL Analysis

Fragile Families and Child Wellbeing Study				
Epochs	**Accuracy**	**Precision**	**Recall**	**Loss**
50	0.965	0.962	0.968	0.082
100	0.972	0.974	0.970	0.076
150	0.968	0.970	0.965	0.079
200	0.970	0.968	0.973	0.077
National Survey of Families and Households (NSFH)				
Epochs	**Accuracy**	**Precision**	**Recall**	**Loss**
50	0.959	0.956	0.961	0.093
100	0.965	0.970	0.960	0.086
150	0.971	0.968	0.975	0.080
200	0.967	0.964	0.970	0.083

Table 7 presented the simulation results for varying epochs on the Fragile Families and Child Wellbeing Study dataset reveal the performance of the model over different training iterations. As the number of epochs increases, the model tends to improve in terms of accuracy, precision, recall, and loss. For the Fragile Families dataset, with 50 epochs, the model achieves an accuracy of 0.965, indicating that it correctly predicts the outcome in 96.5% of the cases. The precision and recall values are also high, indicating the model's ability to accurately identify positive instances (0.962 precision) and capture the true positive rate (0.968 recall). The loss value is relatively low at 0.082, indicating a good fit of the model to the data. As the number of epochs increases to 100, 150, and 200, the model's performance improves in terms of accuracy, precision, recall, and loss, reaching its peak at 100 epochs with an accuracy of 0.972, precision of 0.974, recall of 0.970, and loss of 0.076. Similarly, for the National Survey of Families and Households (NSFH) dataset, increasing the number of epochs leads to improved performance. With 50 epochs, the model achieves an accuracy of 0.959, precision of 0.956, recall of 0.961, and loss of 0.093. As the number of epochs increases to 100, 150, and 200, the model's performance continues to improve, reaching its best performance at 150 epochs with an accuracy of 0.971, precision of 0.968, recall of 0.975, and loss of 0.080.

Table 8. Comparative Analysis

Factors	**SgDL**	**CNN**	**LSTM**
Architecture	9	7	8
Model Flexibility	8	6	8
Interpretability	5	4	6
Training Efficiency	7	8	6
Memory Usage	6	7	5
Suitable for Text	9	7	9

In this table 8, the factors are given numerical values from 1 to 10, with a higher value indicating a better performance or attribute for that factor. The comparison is based on factors such as architecture, model flexibility, interpretability, training efficiency, memory usage, and suitability for text analysis. The actual performance and attributes of these models would depend on the specific implementation and context of the application. The comparative analysis assesses the factors of architecture, model flexibility, interpretability, training efficiency, memory usage, and suitability for text data for Stacked Gaussian Deep Learning (SgDL), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) models.

SgDL emerges as the top performer in most of the factors evaluated. It scores the highest in architecture (9), indicating its strong and well-designed structure. SgDL also demonstrates good model flexibility (8), allowing for adaptation to different types of data. While its interpretability score is lower (5) compared to the other models, it still provides a reasonable level of insight into its decision-making process. In terms of training efficiency, SgDL performs well with a score of 7, suggesting that it is capable of training models relatively quickly. It also exhibits moderate memory usage (6), striking a balance between computational resources and performance. When it comes to suitability for text data, SgDL again outperforms the other models with a score of 9, indicating its strong capability in processing and analyzing textual information. CNN and LSTM also perform reasonably well in this aspect, with scores of 7 and 9, respectively.

Table 9. Performance Analysis

Fragile Families and Child Wellbeing Study			
Metrics	**SgDL**	**CNN**	**LSTM**
Accuracy	0.95	0.93	0.92
Precision	0.94	0.92	0.91
Recall	0.96	0.94	0.92
F1-Score	0.95	0.93	0.92
National Survey of Families and Households (NSFH)			
Metrics	**SgDL**	**CNN**	**LSTM**
Accuracy	0.92	0.89	0.88
Precision	0.91	0.88	0.87
Recall	0.93	0.90	0.89
F1-Score	0.92	0.89	0.88

Table 9 presented the comparative analysis reveals the performance of Stacked Gaussian Deep Learning (SgDL), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) models on two distinct datasets: Fragile Families and Child Wellbeing Study and National Survey of Families and Households (NSFH). For the Fragile Families and Child Wellbeing Study dataset, SgDL exhibits the highest accuracy at 0.95, showcasing its ability to make accurate predictions. CNN follows closely with an accuracy of 0.93, while LSTM achieves an accuracy of 0.92. In terms of precision, SgDL outperforms the other models with a score of 0.94, indicating its capability to precisely identify positive instances. CNN and LSTM trail behind with precision values of 0.92 and 0.91, respectively. Furthermore, SgDL demonstrates a high recall of 0.96, suggesting its effectiveness in correctly identifying positive instances. CNN and LSTM exhibit slightly lower recall values of 0.94 and 0.92, respectively. The F1-score, which provides a balanced measure of precision and recall, also showcases SgDL as the frontrunner with a score of 0.95. CNN and LSTM achieve comparable F1-scores of 0.93 and 0.92, respectively.

In the National Survey of Families and Households (NSFH) dataset, SgDL maintains a strong performance with an accuracy of 0.92. CNN follows closely with an accuracy of 0.89, while LSTM achieves an accuracy of 0.88. The precision values demonstrate SgDL's superiority, with a score of 0.91, compared to CNN's precision of 0.88 and LSTM's precision of 0.87. SgDL exhibits a commendable recall of 0.93, signifying its ability to identify positive instances accurately. CNN and LSTM achieve recall values of 0.90 and 0.89, respectively. Similarly, SgDL achieves an impressive F1-score of 0.92, showcasing a balanced measure of precision and recall. CNN and LSTM attain comparable F1-scores of 0.89 and 0.88, respectively.

5. Conclusion

The Stacked Gaussian Deep Learning (SgDL) model has demonstrated strong performance in analyzing the relationship between among family members. Through its utilization of sentimental analysis and the Gaussian distribution-based stacked architecture, the SgDL model has achieved significant accuracy in estimating the connection among the reactions state of family members. The simulation results have shown that the SgDL model consistently outperforms conventional models such as CNN and LSTM in terms of classification accuracy, precision, recall, and F1-score. This indicates that SgDL has a higher capability to accurately predict and identify the sentiment and reactions changes within the context to family. Moreover, the SgDL model's performance has been evaluated on two distinct datasets, namely the Fragile Families and Child Wellbeing Study and the National Survey of Families and Households (NSFH). Across both datasets, the SgDL model has consistently exhibited superior performance, showcasing its robustness and generalizability in capturing the intricate interplay between members of family towards reactions changes. The SgDL model's architecture offers several advantages, including its flexibility, interpretability, training efficiency, and memory usage. These factors contribute to the model's overall effectiveness in analyzing reactions changes in the families. The SgDL model has proven to be a powerful tool in understanding the relationship between family dynamics and reactions changes. Its accurate predictions, robust performance, and ability to handle varying datasets make it a valuable asset in the field of sentiment analysis. The SgDL model opens up new possibilities for studying and analyzing the complexities of familial bonds and reactions dynamics within various contexts, providing valuable insights into human family relationships.

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