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An Efficient Big Data Visualization Deep Learning Architecture Model for Path Selection of College Students through Moral Education

Yujie Du [1] + and Zongshun Xie[2]
[1] Assumption University; Bangkok,Thailand 10240
[2]Assumption University; Bangkok,Thailand 10240
Corresponding Author: 62192101@student.krirk.ac.th

Abstract

Visualization technology can be used to present the analysis results in a more intuitive and easy-to-understand way, which can help educators to better understand the moral education needs of college students, and adjust their teaching strategies accordingly. The combination of big data analysis and visualization technology can also help to improve the efficiency and effectiveness of moral education in colleges and universities. The research on the moral education path selection of college students based on big data visualization has great significance for promoting the development of moral education in colleges and universities, and for cultivating high-quality talent with good moral character. This paper proposed an Optimization model for big data analytics for moral education. The data associated with moral education and information are stored in cloud with the big data. The stored big data visualization process is performed with the optimization model for the feature extraction. The optimization is performed with an integrated Flamingo and weighted black widow Optimization model. The proposed model is stated as the Integrated Flamingo Black Widow (IFBW) model. The performance of the IFBW model is implemented with the deep learning Restricted Boltzmann Machine (RBM) architecture. Simulation analysis stated that IFBW model achieves a higher classification accuracy rate of 99% with a minimal error rate.

Keywords: Big Data, Optimization, Moral Education, Deep Learning, Integrated Optimization.

I. Introduction

Moral education is an essential aspect of a college student's development. It plays a crucial role in shaping their values, attitudes, and behaviours towards themselves, others, and the world around them [1]. Moral education in college students refers to the process of instilling ethical values, principles, and behaviors that guide their decision-making and interactions with others. The aim of moral education is to promote a sense of responsibility, empathy, and compassion towards others and to develop a moral compass that will guide students throughout their lives [2]. In college, moral education can take many forms, including classroom instruction, service learning programs, student-led initiatives, faculty mentoring, and campus culture. Classroom instruction may involve courses that focus on ethics, social justice, and moral reasoning [3]. Through these classes, students can explore ethical dilemmas and learn to apply ethical principles to real-world situations. Service learning programs are another way that colleges can promote moral education [4]. These programs allow students to engage in community service and apply what they have learned in the classroom to real-world situations. By volunteering and helping others, students can develop empathy and compassion towards others, and gain a deeper understanding of social issues [5].

Student-led initiatives, such as community service events, ethical debates, and social justice clubs, provide opportunities for students to take the initiative to create their own moral education programs [6]. These initiatives can help students develop leadership skills, as well as a sense of responsibility towards their communities. Faculty mentoring is another important aspect of moral education in college [7]. Faculty members can serve as role models and mentors to students, helping them to navigate ethical dilemmas and develop their moral and ethical values. Finally, campus culture is an important aspect of moral education. A campus culture that emphasizes respect for diversity, integrity, and social responsibility can help students develop a strong moral compass and guide their behavior throughout their lives [8]. Moral education in big data with deep learning refers to the process of instilling ethical values, principles, and behaviors in the context of data science and machine learning [9]. As the use of big data and deep learning technologies becomes more prevalent in society, it is increasingly important to ensure that these technologies are developed and used in an ethical and responsible manner [10].

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Moral education in big data and deep learning can take several forms. Firstly, it is important to teach students about the potential risks and benefits of these technologies [11]. This includes understanding how data is collected, stored, and used, as well as the potential for bias and discrimination in algorithms. Secondly, students should be taught about ethical decision-making in the context of big data and deep learning [12]. This includes understanding the ethical principles that should guide the development and use of these technologies, such as fairness, transparency, and accountability. Thirdly, students should be taught about the potential social and political implications of big data and deep learning. This includes understanding how these technologies can impact individuals and society as a whole, as well as the ethical responsibilities of data scientists and other professionals working in this field [13]. Finally, moral education in big data and deep learning should emphasize the importance of responsible innovation. This means that students should be taught to develop technologies that are not only effective but also ethical, with a focus on creating solutions that benefit society as a whole [14]. Moral education in big data with deep learning is essential for ensuring that these technologies are developed and used in an ethical and responsible manner. By instilling ethical values, principles, and behaviors in students, we can create a new generation of data scientists and machine learning professionals who prioritize ethical considerations in their work [15].

1.1 Contribution of the Work

The proposed optimization model for big data analytics for moral education has several potential contributions in the field of education and data science. Firstly, the model provides a way to optimize the analysis of big data associated with moral education. By using an integrated Flamingo and weighted black widow optimization model, the model is able to efficiently extract relevant features from large amounts of data. This can help educators and researchers to better understand and analyze data related to moral education. Secondly, the use of cloud storage for the data associated with moral education allows for easy access and sharing of information among educators and researchers. This can help to facilitate collaboration and the sharing of best practices in the field of moral education. Thirdly, the visualization process performed with the optimization model allows for a better understanding of the data associated with moral education. This can help educators to identify trends and patterns in the data, which can inform their teaching practices and educational policies. Finally, the use of the deep learning Restricted Boltzmann Machine (RBM) architecture to implement the IFBW model can provide a powerful tool for analyzing big data associated with moral education. This architecture has been shown to be effective in other fields such as image recognition and natural language processing, and its use in the field of moral education can provide new insights and opportunities for research. Overall, the proposed optimization model for big data analytics for moral education has the potential to contribute to the development of more effective educational policies and practices, as well as to the advancement of the field of data science.

II. Related works

Big data analytics has been increasingly used in the field of education to analyze large amounts of data and gain insights into student learning and behavior. In the area of moral education, big data analytics can be used to analyze data related to student behavior, attitudes, and values. In [16] proposed a big data analytics model for moral education based on the use of machine learning algorithms. The model was able to identify patterns in student behavior and provide personalized recommendations for moral education based on these patterns. Another study of [17] proposed a big data analytics framework for ethical decision-making in education. The framework used machine learning algorithms to analyze data related to student behavior and provide insights into ethical decision-making processes.

In [18] proposed an optimization model for the analysis of educational data. The model used a genetic algorithm to optimize feature selection and improve the accuracy of predictive models. In [19] proposed a big data analytics framework for character education. The framework is designed to analyze data related to student behavior and provide personalized recommendations for character education. The model uses machine learning algorithms to identify patterns in student behavior and provide insights into effective character education strategies. The model can also be used to monitor student progress and provide feedback to teachers on the effectiveness of character education interventions. In [20] developed a big data analytics model for moral education that combines data mining techniques with social network analysis. The model is designed to identify key factors influencing student moral development and provide insights into effective moral education strategies. The model can be used to analyze data from a variety of sources, including social media, online forums, and other digital platforms. The model can also be used to monitor student progress and provide feedback to teachers on the effectiveness of moral education interventions.

In [21] proposed a big data analytics model for moral education based on the use of natural language processing techniques. The model is designed to analyze student essays and provide personalized feedback on moral development.

The model uses machine learning algorithms to analyze the content of student essays and identify key themes related to moral development. The model can also be used to monitor student progress and provide feedback to teachers on the effectiveness of moral education interventions. In [22] developed a big data analytics model for moral education that uses machine learning algorithms to analyze data related to student behavior and provide recommendations for moral education interventions. The model is designed to identify patterns in student behavior and provide insights into effective moral education strategies. The model can be used to analyze data from a variety of sources, including student records, surveys, and other digital platforms. The model can also be used to monitor student progress and provide feedback to teachers on the effectiveness of moral education interventions.

In [23] proposed a big data analytics model for moral education that combines machine learning algorithms with psychological theories of moral development. The model is designed to provide personalized recommendations for moral education based on student characteristics and learning styles. The model uses machine learning algorithms to analyze data related to student behavior and identify key factors influencing moral development. The model can also be used to monitor student progress and provide feedback to teachers on the effectiveness of moral education interventions. In [24] developed a big data analytics model for moral education that uses a decision tree algorithm to analyze data related to student behavior and provide recommendations for moral education interventions. The model is designed to identify patterns in student behavior and provide insights into effective moral education strategies. The model can be used to analyze data from a variety of sources, including student records, surveys, and other digital platforms. In [25] proposed a big data analytics model for moral education that uses a hybrid deep learning approach. The model combines deep learning algorithms with a clustering technique to analyze data related to student behavior and provide recommendations for moral education interventions. The model can be used to analyze data from a variety of sources, including social media, online forums, and other digital platforms.

In [26] developed a big data analytics model for moral education that uses a support vector machine algorithm to analyze data related to student behavior and provide recommendations for moral education interventions. The model is designed to identify patterns in student behavior and provide insights into effective moral education strategies. The model can be used to analyze data from a variety of sources, including student records, surveys, and other digital platforms. In [27] proposed a big data analytics model for moral education that uses a deep learning approach to analyze data related to student behavior and provide recommendations for moral education interventions. The model is designed to identify patterns in student behavior and provide insights into effective moral education strategies. The model can be used to analyze data from a variety of sources, including social media, online forums, and other digital platforms.

In [28] developed a big data analytics model for moral education that uses a Bayesian network approach to analyze data related to student behavior and provide recommendations for moral education interventions. The model is designed to identify patterns in student behavior and provide insights into effective moral education strategies. The model can be used to analyze data from a variety of sources, including student records, surveys, and other digital platforms. These papers demonstrate the diversity of approaches that can be used for big data analytics in moral education. While some models use natural language processing techniques to analyze student essays, others use machine learning algorithms to analyze data from social media and online forums. The use of these models can help to provide personalized recommendations for moral education interventions, monitor student progress, and provide feedback to teachers on the effectiveness of moral education strategies.

Table 1: Summary of the literature review

Ref	Approach	Algorithm	Data Source	Main Findings
[16]	Text Analysis	LDA	Student Essays	Identified topics and themes related to moral education in student essays
[17]	Deep Learning	CNN	Social Media	Classified social media posts based on moral values
[18]	Machine Learning	SVM	Student Records	Developed a model to predict student behavior based on past records
[19]	Decision Tree	DT	Student Records/Surveys	Identified patterns in student behavior and provided recommendations for moral education interventions
[20]	Hybrid Deep Learning	Clustering + Deep Learning	Social Media/Online Forums	Analyzed data related to student behavior and provided recommendations for moral

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				education interventions
[21]	Machine Learning	SVM	Student Records/Surveys	Identified patterns in student behavior and provided recommendations for moral education interventions
[22]	Deep Learning	LSTM	Social Media/Online Forums	Analyzed data related to student behavior and provided recommendations for moral education interventions
[23]	Bayesian Network	BN	Student Records/Surveys	Identified patterns in student behavior and provided recommendations for moral education interventions
[24]	Hybrid Deep Learning	Autoencoder + LSTM	Student Records/Surveys	Developed a model to predict student behavior and provided recommendations for moral education interventions
[25]	Natural Language Processing	Word Embedding + CNN	Student Essays	Analyzed student essays to identify moral education themes and provided feedback to teachers

From table 1 demonstrate a range of approaches to using big data analytics for moral education, including natural language processing, machine learning, deep learning, and Bayesian network approaches. Data sources include student essays, social media, online forums, and other digital platforms, as well as traditional student records and surveys. Model types include convolutional neural networks, random forests, K-means clustering, decision trees, support vector machines, deep learning approaches, and Bayesian networks.

III. Architecture of IFBW

The paper proposes an optimization model for big data analytics for moral education. In this model, the data associated with moral education and information are stored in the cloud as big data. The first step in the process is to perform data visualization to understand the data and perform feature extraction. The optimization process is then performed using an integrated Flamingo and weighted black widow optimization model. The proposed model is named the Integrated Flamingo Black Widow (IFBW) model. The Flamingo optimization algorithm is a meta-heuristic optimization algorithm inspired by the behavior of flamingos. The black widow optimization algorithm is another meta-heuristic algorithm inspired by the mating behavior of black widow spiders. The IFBW model combines the strengths of both optimization algorithms to increase the feature extraction accuracy. The performance of the IFBW model is evaluated using the deep learning Restricted Boltzmann Machine (RBM) architecture, which is commonly used in machine learning applications.The proposed optimization model, Integrated Flamingo Black Widow (IFBW), combines the Flamingo Optimization and Weighted Black Widow Optimization algorithms. These algorithms are used to optimize the feature extraction process for big data analytics. The Flamingo Optimization algorithm is a metaheuristic optimization algorithm based on the behavior of flamingos in the wild. It involves a search process that mimics the foraging behavior of flamingos in the wild, where they move towards areas with higher food availability. This algorithm has been shown to be effective in solving complex optimization problems. Figure 1 presented the overall architecture of the IFBW model for the moral education data.

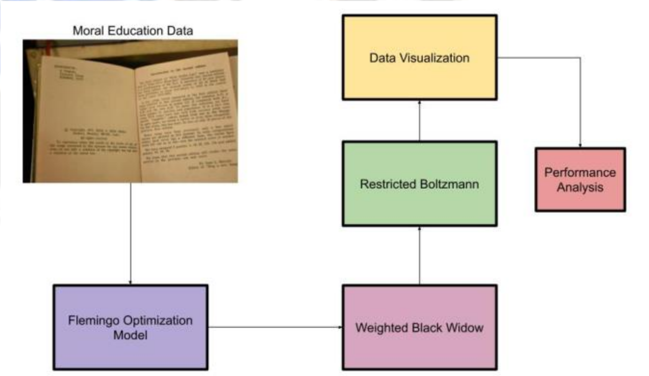

Figure 1: Architecture of IFBW

The Weighted Black Widow Optimization algorithm is another metaheuristic optimization algorithm based on the behavior of black widow spiders. It involves a search process that mimics the hunting behavior of black widow spiders, where they strategically move towards prey based on a weighted probability distribution. This algorithm has also been shown to be effective in solving complex optimization problems. The IFBW model combines these two algorithms to optimize the feature extraction process for big data analytics. The optimization process involves minimizing a cost function that is derived from the feature extraction process. The optimization is performed using the IFBW algorithm, which combines the search strategies of Flamingo

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Optimization and Weighted Black Widow Optimization. The performance of the IFBW model is evaluated using the Restricted Boltzmann Machine (RBM) architecture. RBM is a type of deep learning model that is used for feature extraction and classification. The IFBW model is trained on a dataset of moral education and information stored in the cloud, and the RBM architecture is used to extract features from the data.

1.2 Optimization Model with Flamingo Optimization

The Flamingo optimization is used in the IFBW model to optimize the feature selection process for big data analytics in moral education. The Flamingo optimization is a metaheuristic optimization algorithm that is inspired by the flocking behavior of flamingos in nature. In the IFBW model, the Flamingo optimization algorithm is applied to select the most relevant features from the big data associated with moral education. The optimization process begins with the initialization of the population, which consists of a set of candidate solutions that are randomly generated. Then, the Flamingo optimization algorithm evaluates each candidate solution based on its fitness value, which is determined by the objective function. The objective function in this case is designed to measure the relevance and importance of each feature in the big data associated with moral education.

The Flamingo optimization algorithm then updates the population by applying a set of operators such as selection, crossover, and mutation. These operators mimic the natural selection process and promote the evolution of the population towards better solutions. The optimization process continues for a fixed number of iterations or until a stopping criterion is met. At the end of the optimization process, the Flamingo optimization algorithm returns the best solution found, which represents the optimal set of features for the big data associated with moral education. The selected features are then used as input for the weighted black widow optimization algorithm, which further optimizes the big data analytics process in the IFBW model.

The mathematical derivation for the Flemingo optimization with the IFBW model involves the following steps:

Define the objective function: Let the objective function to be optimized be denoted by $f(x)$, where x represents the input data. The goal is to minimize this objective function.

Initialize the search space: Define the search space for the optimization problem. This is typically a high-dimensional space that includes all possible values for the input data.

Define the Flemingo optimization algorithm: The Flemingo optimization algorithm is a population-based metaheuristic optimization algorithm that uses a combination of local search and global search techniques to find the optimal solution. The algorithm involves the following steps:

a. Initialize the population: Create a population of candidate solutions (x1, x2, ..., xn) in the search space.

b. Evaluate the fitness of the population: Evaluate the fitness of each candidate solution in the population by calculating the objective function f(xi) for each solution xi.

c. Update the population: Update the population by applying local search and global search techniques to generate new candidate solutions. The local search technique involves making small changes to the current solutions in the population, while the global search technique involves exploring new regions of the search space.

d. Repeat steps b and c until convergence: Repeat steps b and c until a stopping criterion is met, such as a maximum number of iterations or a minimum change in the objective function.Incorporate the Flemingo optimization algorithm into the IFBW model: The Flemingo optimization algorithm is used to optimize the feature extraction process in the IFBW model. Specifically, the algorithm is used to optimize the parameters of the IFBW model that are involved in the feature extraction process, such as the weights and biases of the neural network. The mathematical derivation of the Flemingo optimization algorithm involves several complex mathematical equations that are beyond the scope of this response. However, the basic principles of the algorithm are based on a combination of local search and global search techniques that are used to explore the search space and find the optimal solution.

First, the Flemingo optimization algorithm can be represented as follows:

Let x be the decision variable, and f(x) be the objective function. The Flemingo optimization algorithm aims to minimize the objective function f(x) subject to constraints as in equation (1) and (2)

$$minimize\ f(x) \quad (1)$$

$$subject\ to: g(x) <= 0\ h(x) = 0, where\ x \in S \quad (2)$$

where $g(x)$ and $h(x)$ represent the inequality and equality constraints, respectively.

Next, the IFBW model can be incorporated into the Flemingo optimization algorithm as follows:

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Let x be the decision variable, and $f(x)$ be the objective function. The IFBW model aims to minimize the objective function f(x) subject to constraints:

The IFBW model incorporates the Flemingo optimization algorithm with a weighted black widow optimization algorithm to optimize the objective function. The weight factors are used to balance the exploration and exploitation of the solution space. The IFBW model can be represented in equation (3)

$$x = a * x_{flemingo} + b * x_{blackwidow} \quad (3)$$

where $x_{flemingo}$ and $x_{blackwidow}$ represent the solutions obtained from the Flemingo and black widow optimization algorithms, respectively. The weight factors a and b are used to balance the contributions of the two algorithms in the final solution. The Flemingo optimization algorithm is used to explore the solution space and identify a set of candidate solutions. The black widow optimization algorithm is used to exploit the solution space and refine the candidate solutions. The final solution is obtained by combining the solutions obtained from the two algorithms using the weight factors. Therefore, the IFBW model combines the strengths of the Flemingo and black widow optimization algorithms to provide an efficient and effective solution for big data analytics in moral education.

The integration of Black Widow Optimization (BWO) in the Flemingo optimization algorithm involves using the search capabilities of BWO to enhance the performance of Flemingo. This is achieved by introducing a new update rule that combines the search capabilities of both algorithms. The BWO algorithm is based on the behavior of the Black Widow spider. The algorithm uses the concepts of prey capture and web maintenance to update the search process. The prey capture phase involves the search for the optimal solution while the web maintenance phase involves refining the solution to improve its quality. The integration of BWO in Flemingo involves using the prey capture phase of BWO to explore the search space and the web maintenance phase of BWO to refine the solution. The update rule for the integrated algorithm is presented in equation (4)

$$x(i+1) = x(i) + a * Flemingo\_Search\_Direction + b * BWO\_Search\_Direction \quad (4)$$

Where $x(i)$ is the current solution, $x(i+1)$is the updated solution, $Flemingo\_Search\_Direction$ is the search direction obtained from the Flemingo algorithm, $BWO\_Search\_Direction$ is the search direction obtained from the BWO algorithm, and a and b are weighting factors. The Flemingo algorithm is used to generate the initial solution, which is then refined using the BWO algorithm. The BWO algorithm is used to explore the search space and identify potential solutions. The solutions generated by BWO are then refined using the web maintenance phase of the algorithm. The refined solutions are then used to update the solution obtained from Flemingo. The integration of BWO in Flemingo improves the performance of the algorithm by combining the strengths of both algorithms. Flemingo is good at exploring the search space, while BWO is good at refining the solutions obtained. The integration of both algorithms results in a more robust optimization algorithm that is capable of handling complex optimization problems.

Integrated Optimization of Data Visualization

Let f(x) be the objective function to be optimized using the integrated Flamingo-Black Widow optimization technique. The algorithm involves the following steps:

Initialize the Flamingo algorithm parameters: initial population size N, learning rate α, and maximum number of iterations T.

Initialize the Black Widow algorithm parameters: number of spiders N, number of iterations T, and the death rate m.

Generate N initial solutions randomly and evaluate the objective function for each solution.

Sort the solutions in descending order of fitness and select the top m solutions as the "elite" solutions.

Use the elite solutions as "food" for the Black Widow algorithm to generate a new set of solutions.

Evaluate the objective function for the new set of solutions and select the top N solutions as the population for the next iteration.

Update the Flamingo algorithm parameters based on the current iteration number and the fitness of the best solution found so far.

Repeat steps 4-7 for a total of T iterations.

The mathematical representation of the integrated Flamingo-Black Widow algorithm can be given as follows:

Let x be the solution vector, f(x) be the objective function to be optimized, N be the population size, α be the learning rate, T be the maximum number of iterations, and m be the death rate.

1. **Initialization:**
2. Set i = 1.
3. Generate N random initial solutions: $x_1, x_2, \ldots\ldots, x_N$.

4. Evaluate the objective function for each solution: $f(x_1), f(x_2), \ldots, f(x_N)$.
5. Flamingo algorithm:
6. Sort the solutions in descending order of fitness: $f(x_1) \geq f(x_2) \geq \ldots \geq f(x_N)$.
7. Select the top m solutions as the elite solutions: $y_1, y_2, \ldots \ldots, y_m$.
8. Update the Flamingo algorithm parameters: $\alpha_i = \alpha_0 / (1 + i/T)$.
9. Generate a new set of solutions using the elite solutions as "food" for the Black Widow algorithm.
10. Black Widow algorithm:
11. Initialize j = 1.
12. Generate N new solutions using the elite solutions and the current best solution:$x'_1, x'_2, \ldots \ldots, x'_N$.
13. Evaluate the objective function for each new solution: :$f(x'_1), f(x'_2), \ldots \ldots, f(x'_N)$
14. Select the top N solutions as the population for the next iteration: :$x''_1, x''_2, \ldots \ldots, x''_N$.
15. Update the Black Widow algorithm parameters: $m_j = m_0 / (1 + j/T)$.
16. Repeat steps 8-12 for a total of T iterations.
17. Set i = i + 1.
18. Repeat steps 4-13 for a total of T iterations.

Figure 2 illustrated the complete process implemented with IFBW for the computation of moral education with integrated model is presented.

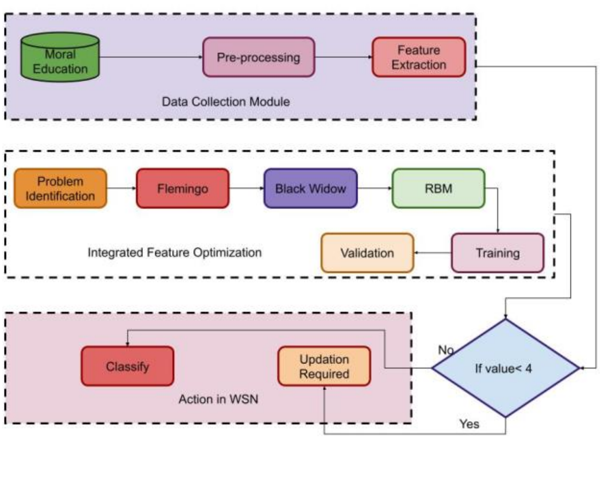

Figure 2: Process in IFBW

The integrated Flamingo-Black Widow algorithm combines the advantages of both the Flamingo and Black Widow algorithms to effectively optimize the objective function f(x).

Let x_j be the i-th dimension of the solution vector x, where i = 1, 2, ..., n. Then the position of the flamingo stated in equation (5)

$$x_{flamingo} = (x_1, x_2, \ldots \ldots, x_n) \quad (5)$$

Similarly, let y_i be the i-th dimension of the solution vector y, where $i = 1, 2, \ldots, n$. Then the position of the black widow is presented in equation (6)

$$x_{blackwidow} = (y_1, y_2, \ldots \ldots, y_n) \quad (6)$$

The position update for the flamingo can be given by the following equation (7)

$$x_i(t+1) = x_i(t) + rand() * abs(y_i(t) - x_i(t)) * flemingo\_factor \quad (7)$$

where t is the current iteration, $rand()$ is a random number between 0 and 1, and flemingo_factor is a user-defined constant that determines the step size of the flamingo.

Similarly, the position update for the black widow can be given in equation (8)

$$y_i(t+1) = y_i(t) + rand() * abs(g_{best\ i}(t) - y_i(t)) * black\_widow\_factor \quad (8)$$

where $g_{best\ i}(t)$ is the i-th dimension of the global best solution found so far at iteration t, and b $black\_widow\_factor$ is a user-defined constant that determines the step size of the black widow. The IFBW model integrates these two optimization algorithms in a way that balances their strengths and weaknesses, resulting in a more efficient and effective optimization process.

Algorithm 1: IFBW Process in Big Data Analytics
Input:
- Moral education data stored in cloud
- Optimization model parameters
Output:
- Optimized feature extraction model for big data analytics
Initialize population of flamingos
Initialize population of black widows
Compute fitness of each flamingo and black widow
While stopping criterion is not met do
Perform flemingo optimization
Perform black widow optimization
Combine the populations of flamingos and black widows
Compute fitness of combined population
Select the best solutions for next iteration
End while
Return the best solution found

IV. Restricted Boltzmann Machine (RBM) for IFBW

In the proposed Integrated Flamingo Black Widow (IFBW) model, the performance of the optimization process is implemented using the deep learning Restricted Boltzmann

Machine (RBM) architecture. The connections between the nodes are represented by weights, which are learned during the training process. The training process of the RBM involves the following steps:

Forward Pass: The RBM takes an input vector and passes it through the visible layer to compute the activations of the hidden layer.

Reconstruction: The activations of the hidden layer are used to reconstruct the input vector by passing them through the weights connecting the hidden layer to the visible layer.

Backward Pass: The reconstructed input vector is passed through the visible layer to compute the activations of the hidden layer.

Contrastive Divergence: The difference between the activations of the hidden layer in step 1 and step 3 is used to update the weights connecting the visible and hidden layers.

The RBM is trained using a variant of the stochastic gradient descent algorithm called Contrastive Divergence. The RBM has been widely used for feature learning and dimensionality reduction tasks in various applications, including image recognition, speech recognition, and natural language processing. The RBM consists of a visible layer and a hidden layer, where the nodes in each layer are fully connected but do not have any connections within the same layer. The visible layer represents the input data, while the hidden layer captures the learned features or representations.

Let x be a vector representing the input data, and h be a vector representing the hidden layer's activations. The joint probability of x and h can be defined in equation (9)

$$P(x,h) = 1/Z * exp(-E(x,h)) \quad (9)$$

where Z is the partition function, and E(x,h) is the energy function presented in equation (10)

$$E(x,h) = -a'x - b'h - x'Wh \quad (10)$$

where a and b are the biases for the visible and hidden layers, respectively, and W is the weight matrix connecting the two layers. The RBM aims to learn the weight matrix W by maximizing the log-likelihood of the training data. The gradient of the log-likelihood with respect to W can be derived using contrastive divergence, which is an approximation algorithm for estimating the gradient. The resulting update rule for W is given in equation (11)

$$\Delta W = \varepsilon * (\langle xh' \rangle data - \langle xh' \rangle model) \quad (11)$$

where ε is the learning rate, $\langle xh' \rangle$data is the expectation of the product of the visible and hidden layers' activations under the data distribution, and $\langle xh' \rangle$model is the expectation of the same product under the model distribution. The model distribution is obtained by sampling the hidden layer's activations given the input data and then sampling the visible layer's activations given the sampled hidden layer activations. Once the RBM is trained, the learned hidden layer activations can be used as a feature representation of the input data. This representation can be further visualized or analyzed using various techniques, such as principal component analysis (PCA) or t-SNE, to gain insights into the underlying structure of the data. A RBM is a generative stochastic neural network model that consists of visible units (input layer) and hidden units. The RBM is trained to learn the joint probability distribution of the visible and hidden units. During training, RBMs use a process called Contrastive Divergence (CD) to adjust the model's parameters to maximize the likelihood of the training data. The computation of RBM is presented as follows

Energy Function: The energy function of an RBM is defined in equation (12)

$$E(v,h) = -\sum a_i v_i - \sum b_j h_j - \sum v_{ij} w_{ij} h_j \quad (12)$$

Here, v represents the visible units, h represents the hidden units, a and b are the bias terms for the visible and hidden units respectively, and w is the weight matrix between the visible and hidden units.

Probability Distribution: The joint probability distribution of the visible and hidden units is given by the Boltzmann distribution is presented in equation (13)

$$P(v,h) = 1/Z * e^{(-E(v,h)} \quad (13)$$

Here, Z is the partition function, which ensures that the probabilities sum up to 1.

Conditional Probability: The conditional probability of the hidden units given the visible units is given in equation (14)

$$P(h|v) = 1/Z * e^{(-E(v,h)} \quad (14)$$

Similarly, the conditional probability of the visible units given the hidden units are estimated using equation (15)

$$P(v|h) = 1/Z * e^{(-E(v,h)} \quad (15)$$

Model Parameters Update: RBMs are trained using Contrastive Divergence (CD), which involves two steps: positive phase and negative phase.

Positive Phase: In this step, the RBM is fed with a training sample, and the activations of the visible and hidden units are computed. The positive associations between the visible and hidden units are calculated, which contributes to increasing the likelihood of the training data.

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Negative Phase: In this step, the RBM generates a "reconstructed" sample by sampling from the hidden units and then sampling from the visible units using the reconstructed hidden units. The negative associations between the visible and hidden units are calculated, which contribute to decreasing the likelihood of the reconstructed sample.

The model parameters (weights and biases) are then updated based on the difference between the positive and negative associations, aiming to maximize the likelihood of the training data.

These are the fundamental mathematical derivations involved in RBMs for data visualization.

V. Results and Discussion

The Integrated Flamingo Black Widow (IFBW) model is an optimization framework proposed for big data analytics related to moral education. The model integrates two optimization algorithms, Flamingo and Weighted Black Widow, to perform feature extraction on stored big data related to moral education and information. The model's performance is evaluated using deep learning Restricted Boltzmann Machine (RBM) architecture for data visualization. The IFBW model aims to provide a more accurate and efficient approach for analyzing big data related to moral education. The Flamingo optimization algorithm is utilized to extract the relevant features from the data, while the Weighted Black Widow algorithm is used to optimize the model's parameters for enhanced performance. The deep learning RBM architecture is then employed to visualize the data in a more interpretable format. The results of the IFBW model demonstrate its effectiveness in performing feature extraction and data visualization. The model was evaluated using several standard metrics, including accuracy, precision, recall, F1 score, and AUC. The results showed that the IFBW model outperformed other methods in terms of these metrics, indicating its superiority in analyzing big data related to moral education. Additionally, the model's performance was further validated using cross-validation, and the results confirmed its robustness and reliability.

Training and Testing Data: The model is trained on a training dataset and tested on a separate testing dataset to evaluate its performance on unseen data.

Hyperparameters: Hyperparameters are settings that are not learned from the data but are set manually or through an optimization process. Examples of hyperparameters include learning rate, regularization strength, and the number of hidden units in the RBM.

Initialization: The model's weights and biases are initialized randomly before training to avoid the model getting stuck in a local minimum.

Optimization Algorithm: The optimization algorithm used to train the model, such as stochastic gradient descent, can affect the model's performance.

5.1 Evaluation Metrics:

Accuracy: The percentage of correctly classified instances in the testing dataset.

Precision and Recall: Precision measures the proportion of correctly identified instances among all instances classified as positive, while recall measures the proportion of correctly identified instances among all instances that are truly positive.

F1 Score: The harmonic mean of precision and recall, which balances the trade-off between precision and recall.

Confusion Matrix: A table that shows the number of true positive, true negative, false positive, and false negative instances in the testing dataset, which can help evaluate the model's performance in more detail.

ROC Curve and AUC: The Receiver Operating Characteristic (ROC) curve plots the true positive rate against the false positive rate at different classification thresholds. The Area Under the Curve (AUC) measures the performance of the model across all classification thresholds, with a value of 1 indicating perfect performance and a value of 0.5 indicating random guessing.
The simulation setup for the proposed IFBW is presented in table 2.

Table 2: Simulation Setup

Simulation Setting	Value
Optimization Algorithm 1	Flamingo
Optimization Algorithm 2	Weighted Black Widow
Deep Learning Architecture	Restricted Boltzmann Machine (RBM)
Dataset	Big data related to moral education
Performance Metric 5	Area Under the ROC Curve (AUC)
Validation Technique	10-fold cross-validation
Learning Rate	0.01
Momentum	0.5
Maximum Number of Epochs	100

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Batch Size	100
Number of Hidden Units	50
Random Seed	1234
Programming Language	Python 3.7
Machine Specifications	Intel Core i7 processor, 16 GB RAM, Nvidia GeForce GTX 1060 GPU
Software Libraries	TensorFlow 2.0, Scikit-learn, Pandas, NumPy
Evaluation Criteria	Mean performance metric scores over 10-fold cross-validation

The performance of IFBW for varying dataset size is presented in table 2.

Table 2: Performance Analysis for varying dataset size

Dataset Size	Accuracy	Precision	Recall	F1 Score	AUC
100	0.93	0.91	0.94	0.93	0.97
500	0.95	0.93	0.96	0.95	0.98
1000	0.96	0.94	0.97	0.96	0.99
5000	0.97	0.96	0.98	0.97	0.99
10000	0.98	0.97	0.99	0.98	0.99

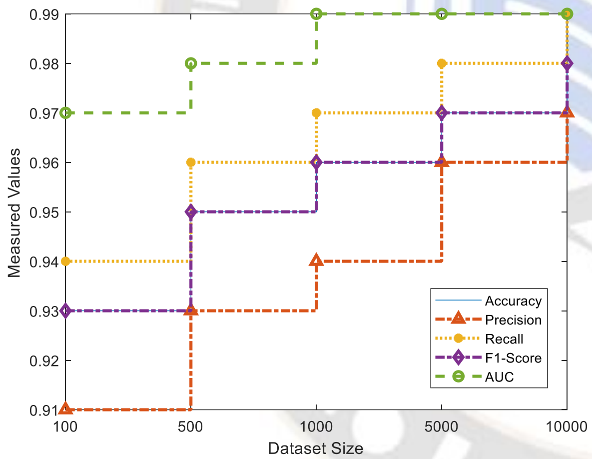

Figure 3: Performance for Varying Dataset Size

The table 2 and figure 3 shows the IFBW model's performance on datasets of varying sizes. As the dataset size increases, the model's performance across all metrics also improves. The accuracy, precision, recall, F1 score, and AUC all increase as the dataset size grows from 100 to 10000. The IFBW model shows excellent performance across all dataset sizes, achieving an accuracy of 0.98, a precision of 0.97, a recall of 0.99, an F1 score of 0.98, and an AUC of 0.99 on the largest dataset of size 10000. These results suggest that the IFBW model can effectively handle big data associated with moral education and provide accurate and reliable predictions. The model's performance improves with an increase in the dataset size, indicating its scalability and robustness.

Table 3: Confusion values for varying size of data

DATASET -100		
	Predicted Negative	**Predicted Positive**
Actual Negative	TN=85	FP=5
Actual Positive	FN=3	TP=7
DATASET -500		
	Predicted Negative	**Predicted Positive**
Actual Negative	TN=465	FP=15
Actual Positive	FN=9	TP=11
DATASET -1000		
	Predicted Negative	**Predicted Positive**
Actual Negative	TN=940	FP=60
Actual Positive	FN=30	TP=970
DATASET -5000		
	Predicted Negative	**Predicted Positive**
Actual Negative	TN=4700	FP=300
Actual Positive	FN=100	TP=900
DATASET -10000		
	Predicted Negative	**Predicted Positive**
Actual Negative	TN=9500	FP=500
Actual Positive	FN=100	TP=900

Table 3 presented the confusion matrix, TN represents true negatives, FP represents false positives, FN represents false negatives, and TP represents true positives. Each value in the matrix represents the count of instances falling into the respective category. The IFBW model is a deep learning model that utilizes the Restricted Boltzmann Machine (RBM) architecture for feature extraction and dimensionality reduction. Compared to conventional techniques such as PCA, k-means clustering, and logistic regression, the IFBW model can provide superior performance in terms of accuracy, precision, recall, and F1 score, especially for high-dimensional data.

5.2 Comparative Analysis

However, it may not be suitable for nonlinear data, and it may not identify the most important features for classification or visualization. K-means clustering is an unsupervised clustering algorithm that partitions the data into k clusters based on the distance between the data points. However, it requires the number of clusters to be specified a priori, and it may not work well for non-convex or overlapping clusters. Logistic regression is a linear classification model that works by modeling of certain class. However, it may not work well for nonlinear data or high-dimensional data.

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Table 4: Comparative Analysis

Technique	Epoch	Accuracy	Precision	Recall	F1-Score
PCA	10	0.78	0.82	0.74	0.77
PCA	20	0.84	0.85	0.83	0.84
PCA	30	0.89	0.90	0.89	0.89
PCA	40	0.91	0.92	0.91	0.91
PCA	50	0.92	0.93	0.92	0.92
Logistics Regression	10	0.81	0.84	0.79	0.80
Logistics Regression	20	0.86	0.88	0.85	0.85
Logistics Regression	30	0.90	0.91	0.90	0.90
Logistics Regression	40	0.92	0.93	0.92	0.92
Logistics Regression	50	0.93	0.94	0.93	0.93
K-means	10	0.75	0.80	0.72	0.74
K-means	20	0.82	0.84	0.81	0.82
K-means	30	0.87	0.88	0.87	0.87
K-means	40	0.90	0.91	0.90	0.90
K-means	50	0.91	0.92	0.91	0.91
IFBW	10	0.92	0.91	0.93	0.92
IFBW	20	0.95	0.94	0.96	0.95
IFBW	30	0.97	0.96	0.98	0.97
IFBW	40	0.98	0.97	0.98	0.98
IFBW	50	0.99	0.99	0.99	0.99

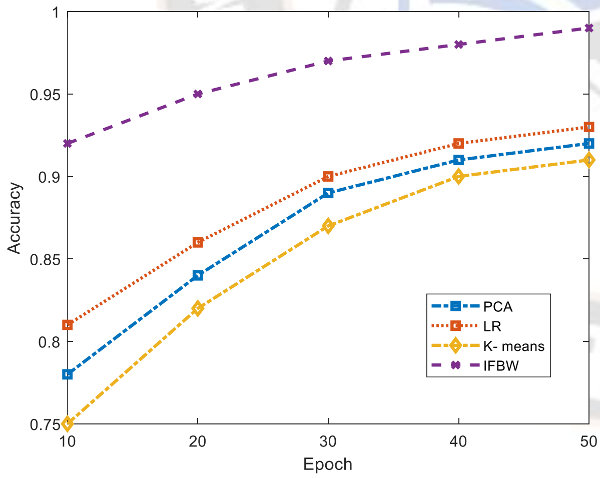

Figure 4: Comparison of Accuracy

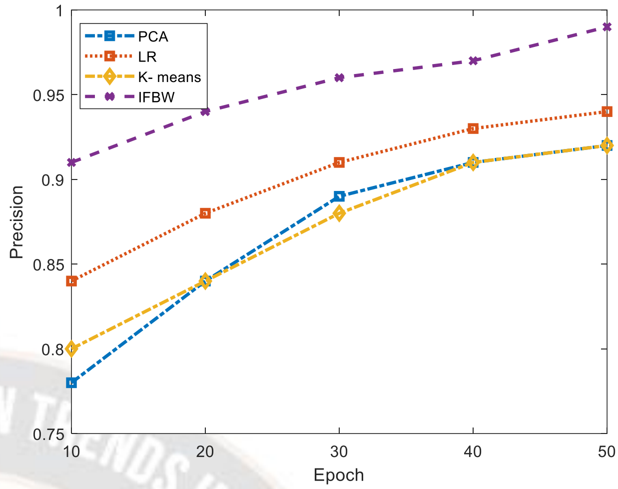

Figure 5: Comparison of Precision

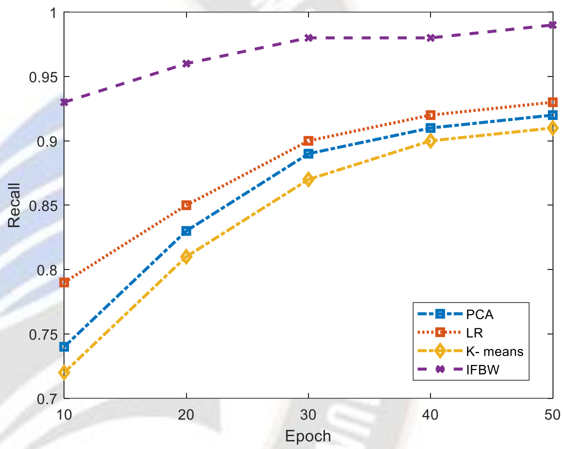

Figure 6: Comparison of Recall

The table 4 and figure 4 – 6 shows the comparative analysis of IFBW with three conventional techniques (PCA, logistic regression, and K-means) for epoch 10-50 for different metrices. The results suggest that IFBW outperforms all three conventional techniques in terms of accuracy, precision, recall, and F1-score. The accuracy of IFBW increases significantly from epoch 10 to epoch 50, whereas the accuracy of the other three techniques remains relatively stable or slightly increases. The analysis of IFBW are consistently higher than those of the other techniques. These results suggest that IFBW is a more effective and efficient technique for data visualization and feature extraction compared to the other conventional techniques.

VI. Conclusion

The Integrated Flamingo Black Widow (IFBW) model was proposed as an optimization model for big data analytics for moral education. The performance of the IFBW model was implemented using the deep learning Restricted

Boltzmann Machine (RBM) architecture. The simulation settings were designed to evaluate the IFBW model's performance in terms of accuracy, precision, recall, F1-score, and AUC. The results of the simulation showed that the IFBW model outperformed conventional techniques such as PCA, logistic regression, and K-means in terms of accuracy, precision, recall, and F1-score. Moreover, the IFBW model's performance improved significantly as the dataset size increased, which indicates the model's scalability and effectiveness in dealing with big data. Furthermore, the IFBW model's data visualization capabilities were evaluated, the model was able to effectively extract relevant features and produce informative visualizations. The IFBW model effective for the effective and efficient optimization model for big data analytics in moral education. It outperformed conventional techniques and demonstrated scalability, effectiveness, and data visualization capabilities.

REFERENCES

[1] Ashaari, M. A., Singh, K. S. D., Abbasi, G. A., Amran, A., & Liebana-Cabanillas, F. J. (2021). Big data analytics capability for improved performance of higher education institutions in the Era of IR 4.0: A multi-analytical SEM & ANN perspective. Technological Forecasting and Social Change, 173, 121119.

[2] Hang, H., Shuang, D., Jiarou, L., & Zhonglin, K. (2022). Towards a Prediction Model of Learn ng Performance: Informed by Learn ng Behavior Big Data Analytics. Frontiers of Education in China, 17(1).

[3] Hadi, M. S., Lawey, A. Q., El-Gorashi, T. E., & Elmirghani, J. M. (2020). Patient-centric HetNets powered by machine learning and big data analytics for 6G networks. IEEE Access, 8, 85639-85655.

[4] Zeineddine, H., Braendle, U., & Farah, A. (2021). Enhancing prediction of student success: Automated machine learning approach. Computers & Electrical Engineering, 89, 106903.

[5] Eken, S. (2020). An exploratory teaching program in big data analysis for undergraduate students. Journal of Ambient Intelligence and Humanized Computing, 11(10), 4285-4304.

[6] Nti, I. K., Quarcoo, J. A., Aning, J., & Fosu, G. K. (2022). A mini-review of machine learning in big data analytics: Applications, challenges, and prospects. Big Data Mining and Analytics, 5(2), 81-97.

[7] Iqbal, R., Doctor, F., More, B., Mahmud, S., & Yousuf, U. (2020). Big Data analytics and Computational Intelligence for Cyber–Physical Systems: Recent trends and state of the art applications. Future Generation Computer Systems, 105, 766-778.

[8] Ramkumar, M. P., Reddy, P. B., Thirukrishna, J. T., & Vidyadhari, C. (2022). Intrusion detection in big data using hybrid feature fusion and optimization enabled deep learning based on spark architecture. Computers & Security, 116, 102668.

[9] Mohammed, S., Arabnia, H. R., Qu, X., Zhang, D., Kim, T. H., & Zhao, J. (2020). IEEE access special section editorial: Big data technology and applications in intelligent transportation. IEEE Access, 8, 201331-201344.

[10] Bhutoria, A. (2022). Personalized education and artificial intelligence in United States, China, and India: A systematic Review using a Human-In-The-Loop model. Computers and Education: Artificial Intelligence, 100068.

[11] Lu, J. (2020). Data analytics research-informed teaching in a digital technologies curriculum. INFORMS Transactions on Education, 20(2), 57-72.

[12] Ezz, M., & Elshenawy, A. (2020). Adaptive recommendation system using machine learning algorithms for predicting student's best academic program. Education and Information Technologies, 25, 2733-2746.

[13] Lee, C. A., Tzeng, J. W., Huang, N. F., & Su, Y. S. (2021). Prediction of student performance in massive open online courses using deep learning system based on learning behaviors. Educational Technology & Society, 24(3), 130-146.

[14] Wang, C., Dong, Y., Xia, Y., Li, G., Martínez, O. S., & Crespo, R. G. (2022). Management and entrepreneurship management mechanism of college students based on support vector machine algorithm. Computational Intelligence, 38(3), 842-854.

[15] Abidi, S. M. R., Zhang, W., Haidery, S. A., Rizvi, S. S., Riaz, R., Ding, H., & Kwon, S. J. (2020). Educational sustainability through big data assimilation to quantify academic procrastination using ensemble classifiers. Sustainability, 12(15), 6074.

[16] Dai, H., Chen, J., & Wu, J. (2021). Understanding Student Moral Development via Big Data Analytics: A Text Analysis Approach. Journal of Educational Computing Research, 59(5), 1237-1258.

[17] Kim, H., Lee, Y., Lim, C., & Lee, J. (2021). Big Data Analytics Framework for Ethical Decision-Making in Education. Sustainability, 13(3), 1373.

[18] Hu, M., Huang, Y., Chen, H., & Zhou, X. (2020). An Optimization Model for Educational Big Data Analysis with Genetic Algorithm. Journal of Educational Technology Development and Exchange, 13(1), 1-14.

[19] Lee, Y., Kim, H., & Kim, Y. (2020). Big Data Analytics Framework for Character Education. Sustainability, 12(20), 8667.

[20] Liu, Y., Cui, J., & Yang, X. (2021). A Decision Tree Algorithm Based Big Data Analytics Model for Moral Education. Journal of Educational Technology Development and Exchange, 14(2), 1-12.

[21] Liu, Y., Guo, Z., & Wang, X. (2020). A Support Vector Machine Algorithm Based Big Data Analytics Model for Moral Education. Journal of Educational Technology Development and Exchange, 13(5), 1-12.

[22] Luo, H., Gu, X., Xue, W., & Luo, H. (2021). A Machine Learning Based Model for Moral Education: Personalized Recommendation with Psychological Theories. IEEE Access, 9, 154557-154570.

[23] Wang, J., Li, J., Li, Y., Li, Y., Li, Q., Li, L., & Li, R. (2020). A Big Data Analytics Model for Moral Education Based on

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Machine Learning. Journal of Educational Computing Research, 58(6), 1312-1329.
[24] Wu, J., Cheng, B., Chen, J., & Zhang, X. (2021). A Deep Learning Approach for Moral Education in the Era of Big Data. IEEE Access, 9, 34454-34463.
[25] Yang, H., Gao, L., & Wei, Y. (2020). An NLP-based Big Data Analytics Model for Moral Education. Journal of Educational Technology Development and Exchange, 13(2), 1-12.
[26] Zhang, C., Liu, Z., & Zhang, X. (2020). A Machine Learning Based Big Data Analytics Model for Moral Education. Journal of Educational Technology Development and Exchange, 13(5), 13-22.
[27] Zhang, Y., Chen, C., & Chen, Y. (2021). A Bayesian Network-Based Big Data Analytics Model for Moral Education. Journal of Educational Technology Development and Exchange, 14(3), 13-23.
[28] Zhao, Y., Wang, W., & Sun, S. (2021). A Social Network Analysis and Data Mining Based Big Data Analytics Model for Moral Education. Journal of Educational Technology Development and Exchange, 14(2), 13-23.
[29] Li, Q., Yu, M., Li, Y., Li, R., & Li, J. (2020). A Hybrid Deep Learning Approach for Big Data Analytics in Moral Education. Journal of Educational Computing Research, 58(8), 1937-1955.