Uncovering Hidden Realities of Child Labor Abuse in Egyptian Workplaces with Machine Learning and Explainable AI

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Abstract

Child labor abuse is a pervasive global problem, especially in Egyptian workplaces, where its bureaucratic processes make it difficult to detect and intervene such phenomena. This research presents an in-depth investigation combining explainable artificial intelligence (XAI) and machine learning (ML) to uncover the hidden reality of child labor exploitation in Egyptian companies. Applying six different machine learning models and analyzing, on a published dataset of mistreatment of employed children in Egypt, Artificial Neural Network (ANN) model turns out to performs better than the other models. It shows improvements in accuracy, precision, recall, F1-score, and AUC, over other models including Random Forest, Support Vector Classifier (SVC), and AdaBoost, with an accuracy of 96.00%. Additionally, Explainable AI methods like SHAPASH analysis offer insightful information about the variables, such as working sector and night shift work, driving abuse predictions. With its data-driven method to reveal hidden realities, this research not only promotes a safer environment for kids in Egyptian workplaces, but also these study findings can be expanded in identifying other form of abuses such as elder abuse, substance abuse and others.

CCS Concepts

• **Computing methodologies** → **Neural networks**; • **Applied computing** → *Sociology*.

Keywords

Child labor abuse, Egyptian workplaces, Machine learning, Explainable AI (XAI), Artificial Neural Network (ANN).

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1 Introduction

Child labor abuse has a terrible impact on the physical, mental, and emotional health of children. Reports of abuse range from physical assault, neglect to sexual exploitation and even trafficking. Negative health effects associated with child labor include poor development, malnourishment, elevated risk of infection and system-specific illnesses, behavioral and mental issues, and lesser coping efficacy [10]. According to estimates from the According to estimates from the International Labour Organisation (ILO), there are about 250 million child laborers all around the world, with at least 120 million of working in situations that have deprived them of a regular childhood and endangered their health or perhaps their lives. Most child labors are between the age of 11 and 14, although 60 million among them are as young as 5 to 11 [3].

The exploitation of children in the labor force not only deprives them of their childhood but also hinders their potential and dignity [13]. The hidden nature of child labor abuse exacerbates the problem, emphasizing the importance of uncovering these hidden realities to effectively address the issue [24].

To address child labor abuse in Egyptian workplaces, the utilization of advanced technologies such as Machine Learning (ML) and Explainable Artificial Intelligence (AI) can be pivotal. ML algorithms can be trained to identify patterns indicative of child labor practices, aiding authorities in detecting and intervening in cases of abuse [12]. Additionally, Explainable AI can offer insights into the decision-making processes of these algorithms, ensuring transparency and accountability in combating child labor abuse [12].

By leveraging ML and Explainable AI, it is feasible to uncover hidden realities of child labor abuse in Egyptian workplaces. These technologies can analyze extensive data sets to pinpoint instances of child labor, comprehend the contributing factors, and propose actionable solutions [11, 26]. Furthermore, the application of ML and Explainable AI can enhance workplace monitoring, guaranteeing compliance with child labor laws and safeguarding children's rights [23].

Apart from the negative impact on child development, child labor hinders the economic growth of a country as well, with reduced skills of the future workforce. Through the application of ML and Explainable AI technologies, stakeholders can identify and eradicate child labor and foster a safe and nurturing environment for children to thrive. This paper provides an insight to different machine learning algorithms in conjunction with explainable artificial intelligence, regarding the child labor abuse issue. The literature review for this study can be found in Section 2, followed by methodology employed in Section 3, experimental results and discussion in Section 4 and the conclusion of the study in Section 5.

2 Literature Review

An exploitation like child labor abuse necessitates innovative solutions to uncover suppressed realities and protect vulnerable children. Machine learning and explainable AI can become a tool for rescue in this regard. By employing data-driven approaches and advanced algorithms, it becomes feasible to detect, categorize, and measure abusive content with high accuracy and scalability [9, 28]. These technologies can play a crucial role in predicting occurrences of various subtypes of child abuse by evaluating demographic and spatial-temporal characteristics of the crimes [20]. Furthermore, machine learning models can assist in the development of systems to detect child abuse and neglect, potentially reducing racial bias and improving interventions in emergency departments [14].

As numerous studies have shown, child abuse—including child labour and sexual abuse is a serious problem in the Great Cairo governorate of Egypt. Low monthly income, migration from rural to urban regions, social customs that support child labour, high school dropout rates, and family breakdown are some of the factors that lead to child labour in Egypt [5].

In Cairo, the majority of child sexual abuse cases involve girls from low socioeconomic backgrounds, particularly adolescents, and anal abuse is a common kind of harm found out by Mohamed, Mahmoud Kamal, et al. [18]. Cairo's working children are susceptible to a range of mistreatment, and child labour is fuelled by parental and child illiteracy . Egypt's government has adopted international conventions, changed policies, and implemented institutional initiatives in an effort to eliminate child labour .

The application of machine learning in detecting abuse extends beyond child labor to various domains such as elder abuse and substance abuse. For example, machine learning has been utilized to identify patterns of healthcare services availed among elder abuse victims, demonstrating the potential for data linkage and advanced algorithms to enhance detection capabilities [16, 25]. Similarly, in the context of substance abuse, deep learning models have been developed to automatically detect nonmedical prescription medication use, from social media data, showcasing the versatility of machine learning in addressing different forms of abuse [1].

Using supervised machine learning models, a novel explainable framework for predicting people's awareness of child abuse can be created [21]. This approach can be used to predict different subtypes of child abuse with high accuracy by utilizing machine learning developments to examine demographic and spatial-temporal factors connected to child abuse events [19]. The approach can offer insights into potential risk factors and preventive interventions by evaluating neurobiological markers linked with persons at high risk of reoffending with child sexual abuse through the application of machine learning techniques [22]. All things considered, a thorough strategy like this can make a substantial contribution to the timely identification and prevention of child sexual abuse by using reliable and understandable predictive models.

Moreover, the ethical considerations of deploying machine learning in sensitive domains like security and abuse detection are paramount. Ensuring that models are interpretable and ethically sound is essential, for maintaining trust and accountability in AI systems [6, 17]. Additionally, addressing the issue of bias in training data and unintended discrimination is crucial to enhancing the fairness and effectiveness of machine learning models in abuse detection [29].

The adoption of cutting-edge technologies opens up promising avenues for developing robust systems capable of identifying, thwarting, and tackling diverse manifestations of abuse. These advanced systems hold the potential to make a significant contribution toward safeguarding and promoting the well-being of vulnerable segments of society. Table 1 and Table 2 summarize the key findings from the literature reviewed in this study.

3 Methodology

This section outlines the methodology undertaken to complete this study. The methodology is comprised of data collection, data preprocessing, machine learning model selection and finally using explainable AI. Figure 1 visually represents the methodology.

3.1 Data Collection and Pre-processing

Our study makes use of a meticulously compiled dataset derived from the investigation "Abuses experienced by child laborers in workplaces in Egypt [15]", which includes 6,224 data points related to abuse factors. The dataset includes information about the child's gender, three educational levels, three parental marital statuses, two parental employment statuses, three occupational sectors, employer gender, and night shift work. To handle categorical data, we used label encoding to convert them to numerical values [27]. With feature engineering, initially composed nine columns, were reduced to the dataset of eight key columns, focusing on influential abuse factors. To ensure model robustness, we divided the dataset into 80% training and 20% test sets, with a 20% validation subset included in the training data. Table 3 shows the data partitioned specifically for model training purposes.

3.2 Comparison and Selection of Prediction Models

We carefully selected six distinct models for our study, utilizing well-known open-source Python libraries. Each model was specifically designed to address and evaluate various aspects of the predictive task at hand.

Random Forest works by generating random subsets of the training data and training a decision tree on each one. Support Vector

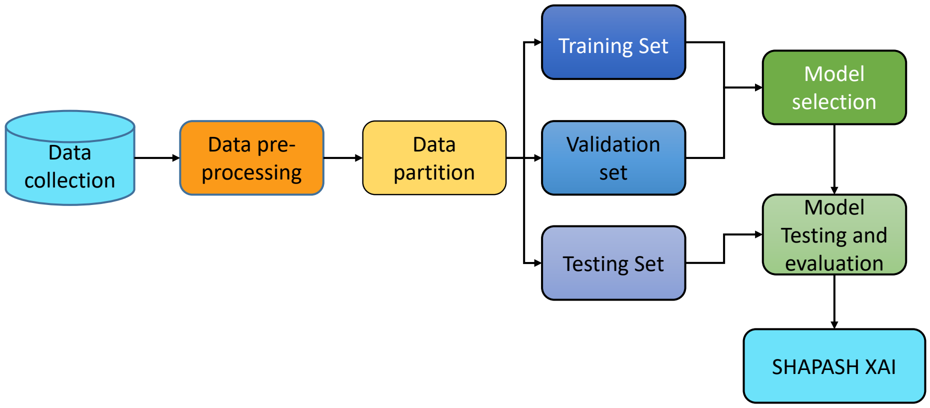


Figure 1: Proposed methodology for child labor abuse in Egyptian workplaces.

Table 1: Summary of Literature Review

Reference	Target	Method	best performance	Motivation
[9] Hossain, M. J. el al.(2022)	predicting suicide terrorist attacks	RF,KNN Decision Tree LightGBM MLP.	accuracy= 98.93%	Absence of machine learning studies on suicide attack success rates.
[28] Vidgen, B. (2020)	Training datasets for detection systems	train abusive language classifiers	Reviews 63 datasets	Reduce the damage caused by hostile online exchanges.
[20] Parthasarathy, S. et al.(2023)	Child abuse prediction	KNN, LR, RF Ensemble	accuracy= 93%	Improving crime prediction methods to focus on child maltreatment prevention.
[16] Miah, M. Saef Ullah, et al.	Medical cyber-physical systems	Machine learning,Cloud and edge computing	presents an adaptive system for post-diagnosis	The system will reduce the need for nurses at the post diagnosis stage
[14] Landau, A. Y.(2023)	child abuse detection	Thematic analysis applied	definitions were explored	Reduce racial bias in machine learning models used to detect child abuse.

Table 2: Summary of Literature Review

Reference	Target	Method	best performance	Motivation
[18] Mohamed, M. K. et al.(2022)	Child sexual abuse	Statistical analysis	Female cases (59.9%) male cases (40.1%)	Recognising the age ranges and gender distribution of victims of sexual abuse.
[5] Landau, Aviv Y., et al.(2023)	Focusing on social and economic factors	Dedoose	Developed Three central themes	Negative Consequences: Stress, Fatigue, Injury, Anemia, Verbal Abuse, Smoking, Violence.

Table 3: Train, Test and Validation split of the employed dataset.

Target Column	Number of Samples	Train	Test	Valid
Child labor abuse	6224	3983	1245	996

Classifier (SVC) works by finding the optimal hyperplane that best separates the different classes in the feature space. k-Nearest Neighbors (KNN) is a simple and straightforward classification algorithm that locates the k-nearest data points in the feature space to a given input point. Logistic Regression uses the logistic function to calculate the likelihood that a given input belongs to a specific class. AdaBoost, or Adaptive Boosting, is an ensemble learning method that combines multiple weak classifiers to produce a strong classifier. All these models are implemented within the scikit-learn library.

In our proposed Artificial Neural Network (ANN) model, we utilized a sequential architecture consisting of densely connected layers. ANN is a computational model based on the structure and function of biological neural networks in the brain. Each node, also known as a neuron, receives input signals, processes them using an activation function, and then forwards the results to the next layer. The output of a neuron in a given layer can be represented as:

$$z = (X \cdot W) + b \tag{1}$$

where z is the weighted sum of inputs and biases. This is then passed through an activation function:

$$a = \sigma(z) \tag{2}$$

In Equations 1 and 2, X is the input data, W represents weights between layers, b is the bias terms, and σ is the activation function, defining key components of our neural network.

3.3 Hyper-Parameters of the models

After selecting the model and setting up the experiment, we refined the hyper-parameters further. This adjustment improved accuracy when compared to the initial default settings.

Table 4: Hyper-parameters Setting for Classification Models.

Model	Hyper-parameter Setting
Random Forest	- `n_estimators`: [50, 100, 200] - `max_depth`: [None, 10, 20] - `min_samples_split`: [2, 5, 10] - `min_samples_leaf`: [1, 2, 4] - `max_features`: ['auto', 'sqrt', 'log2']
Support Vector	- `kernel`: 'rbf' - `C`: 1.0 - `gamma`: 'scale'
K-Nearest Neighbors	- `n_neighbors`: 5
Logistic Regression	- `C`: 1.0 - `penalty`: 'l2' - `solver`: 'liblinear'
AdaBoost	- `n_estimators`: 50
Artificial Neural Network	- `Epochs`: 500 - `Batch Size`: 32 - `Optimizer`: Adam - `Loss Function`: Binary Crossentropy

In table 4, the Random Forest model's hyperparameters, such as {n_estimators}, {max_depth}, {min_samples_split}, {min_samples_leaf}, and {max_features}, control its complexity and generalization. Support Vector Classifier (SVC) hyperparameters, including {kernel}, {C}, and {gamma}, shape decision boundaries, balance training and testing errors, and determine the influence range of individual training examples. K-Nearest Neighbors (KNN) only requires the hyperparameter {n_neighbors}, setting the size of the neighborhood for classification. Logistic Regression's hyperparameters, {C}, {penalty}, and {solver}, control regularization, penalty norm, and optimization, respectively. AdaBoost's hyperparameters include the number of estimators {n_estimators}, which are weak learners used for boosting. Artificial Neural Network (ANN), inspired by biological neural networks, has hyperparameters like {Epochs}, {Batch Size}, {Optimizer}, and {Loss Function}, governing its training process and learning dynamics. The ANN model employs two hidden layers with 128 neurons in the first layer and 64 neurons in the second layer, both using the ReLU activation function.

3.4 Evaluation Metrics

The prediction model has been evaluated using key performance metrics such as accuracy, precision, recall, and F1-score, each of which provides useful information about its effectiveness. Below are the equations of the performance metrics utilized in this study.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{4}$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{5}$$

$$F1\text{-}score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{6}$$

Where false positives are (FP), false negatives are (FN), true positives are (TP) and true negatives are (TN).

Another popular performance metric in machine learning is the Area Under the ROC Curve (AUC). A value greater than 0.5 indicates that the model has predictive power, whereas a value less than 0.5 implies that it performs worse than random guessing.

3.5 Explainable Artificial Intelligence (XAI)

XAI aims to clarify the factors that influence outcomes and the reasoning behind machine learning model decisions. We used SHAPASH, a tool that quantifies feature impact, to explain AI predictions. The SHAPASH Python package was used to assess the significance, direction, and impact of predictors on the target variable [2]. It provides a unified interface for explaining the importance of various features, as well as local and global explanations.

4 Experimental Results and Analysis

In this section, we present a comparative analysis of prediction outcomes across models using SHAPASH explanations as well as the experimental setup design. Our proposed ANN model outperformed others, as described below.

4.1 Experimental setup

In this study, we developed machine learning models using Google Colab [8]. Its free version provided a powerful environment for conducting extensive experiments with minimal resource requirements. Collaboration was facilitated by Colab's features, with all code written in Python3 using Scikit Learn [4, 7].

4.2 Performance of Models

A summary of all models' final prediction results from the testing dataset can be found in Table 3

The performance metrics of each of the six models are contrasted in Table 5. Each model is assessed based on key metrics including precision, recall, F1-score, area under the curve (AUC), and accuracy. Among the models examined, the proposed Artificial Neural Network (ANN) emerges as the top performer across multiple criteria. Notably, the ANN achieves a precision of 0.905, indicating a low rate of false positive predictions, while also demonstrating a recall of 0.977, indicative of a high rate of true positive predictions. This balance between precision and recall is further reflected

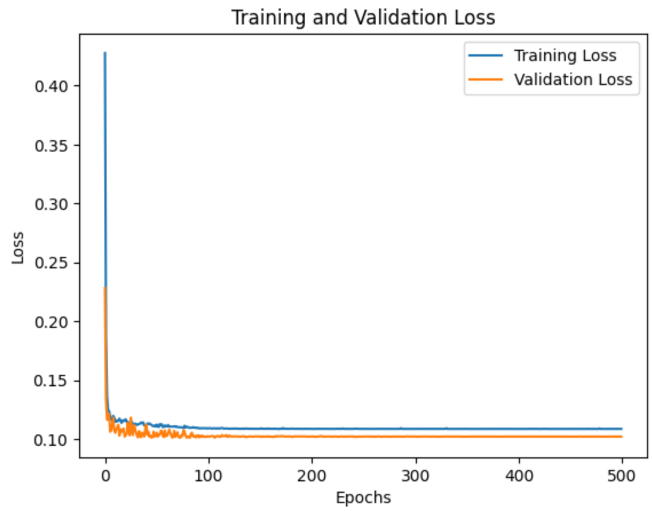
Table 5: All Model's Performance Metrics.

Model	Precision	Recall	F1-score	AUC	Accuracy
Random Forest	0.865	0.951	0.906	0.99	93.17%
SVC	0.890	0.865	0.877	0.95	91.65%
KNN	0.902	0.840	0.870	0.99	91.33%
Logistic Regression	0.817	0.665	0.733	0.91	83.29%
AdaBoost	0.841	1.000	0.903	0.99	93.41%
Proposed ANN	**0.905**	**0.977**	**0.94**	**0.99**	**96.00%**

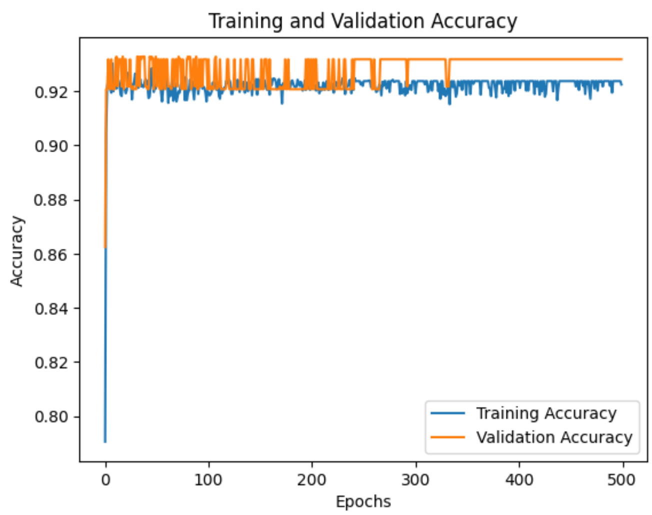
in the ANN's F1-score, which stands at 0.940, the highest among all models. Moreover, the ANN exhibits an AUC of 0.99, underscoring its strong discriminatory capability between positive and negative instances. Importantly, the ANN achieves an accuracy of 96.00%, the highest among all models evaluated. This collective performance underscores the efficacy of the proposed ANN model. This analysis underscores the importance of considering multiple performance metrics to comprehensively assess the effectiveness of machine learning models, particularly in domains where precision, recall, and overall accuracy are critical factors influencing decision-making processes.

Figure 2, shows the training & validation accuracy and loss graphs for the ANN model. In figure 2a, the X-axis spans 0 to 500 epochs, and the Y-axis ranges from 0 to 0.40 loss. The blue line represents training loss, which decreases sharply with increasing epochs. The orange line represents validation loss, which initially decreases and then stabilizes. Figure 2b shows the x-axis ranging from 0 to 500 epochs and the y-axis representing accuracy, which ranges from 0.80 to 0.92. The graph shows a steep rise in both lines from epoch 0, with a plateau at 0.92. Both lines exhibit minimal fluctuations, indicating a well-fitted model with no overfitting or under-fitting.

In Figure 3 depicts data on child labor abuse in Egyptian workplaces. The pie chart in Figure 3a shows that males aged 5 to 11 in elementary school have the most reports of abuse, while females aged 15 to 17 in high school have the fewest. Figure 3b shows the blue line representing "yes" for abuse and the orange line representing "no" abuse across three working sectors. According to the data, the industrial sector has the highest rate of reported abuse, with agriculture coming in second place.



(a) Training and validation loss graph.



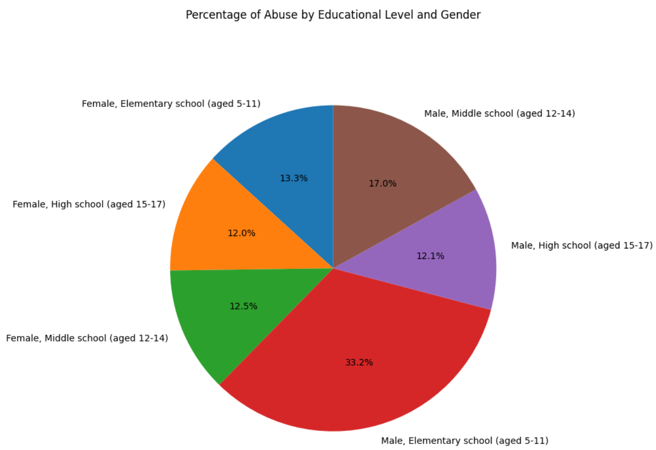
(b) Training and validation accuracy graph.

Figure 2: ANN model's training and validation accuracy and loss graphs.

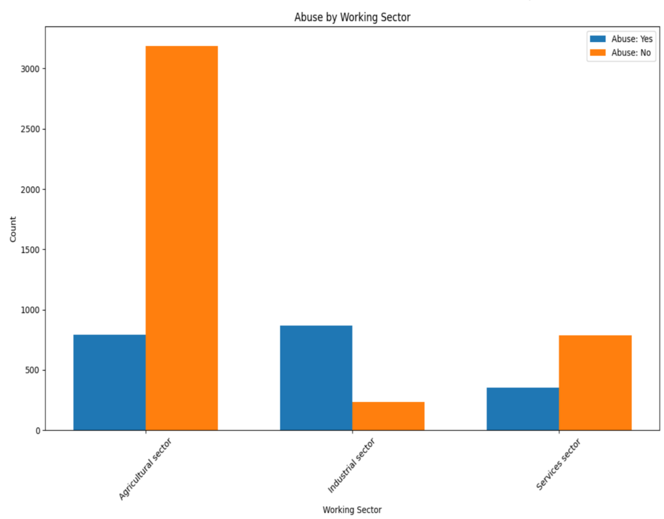
4.3 Using SHAPASH to Interpret ANN Model's Predictions

The analysis of the ANN model's prediction results using SHAPASH yielded insightful findings, as illustrated in Figure 4.

In figure 4a, 'Working sector' emerges as the most influential factor, with a substantial contribution of 0.3509. Following closely behind is 'Work at night shift' with a contribution of 0.3483. Other noteworthy contributors include 'Educational level' (0.1524), 'Parents' employment status' (0.0593), 'Parents' marital status' (0.0439), 'Employer's sex' (0.042), and 'Gender' (0.0025). This analysis underscores the pivotal role of the 'Working sector' variable in the model's predictive accuracy. In Figure 4b, the SHAPASH compare plot requires specific indices to analyze and compare rows of data within the dataset. For instance, ID 1520 exhibits varying contributions from different features towards abuse prediction. Notably, 'Working sector' contributes positively with 0.5076, while 'Work at night shift' shows a negative contribution of -0.1117. Similarly, 'Educational level', 'Employer's sex', and 'Parents' employment status' also display negative impacts, while 'Parents' marital status' and 'Gender' contribute positively. Each ID represents a distinct data instance, with unique feature contributions influencing abuse prediction.

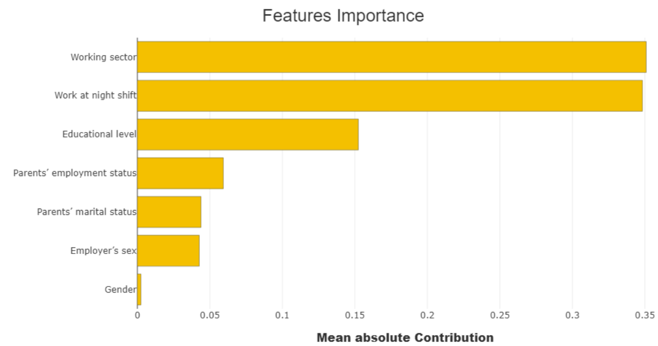


(a) Pie chart for abuse by educational level and gender.

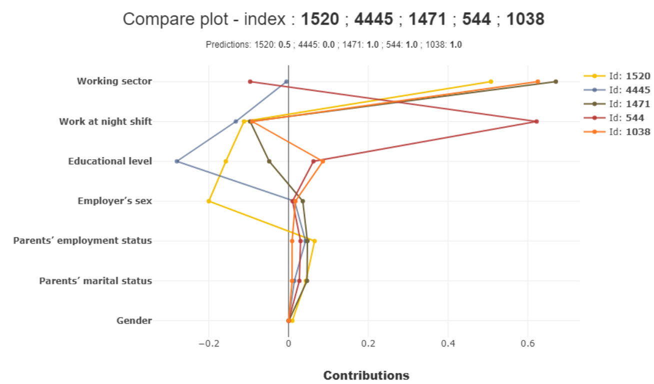


(b) Bar chart for abuse by working sector.

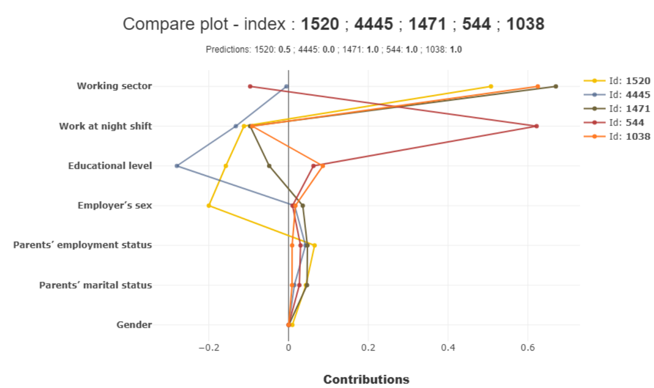
Figure 3: Child labor abuse insights output graph.



(a) SHAPASH features importance plot.



(b) Compare plot for indices - 1520, 4445, 1471, 544, 1038.



(c) Compare plot for indices - 6183, 2072, 4427, 5012, 1912.

Figure 4: SHAPASH plots for the proposed ANN model.

The ANN model outperforms other models when it comes to classifying child labor abuse in Egyptian workplaces. This superiority is clearly demonstrated in Table 5, where the ANN model outperforms all other evaluated models. With superior metrics such as AUC curve and accuracy, the proposed model demonstrates its ability to accurately predict cases of child labor abuse.

Important information about the variables influencing the model's classification is provided by the SHAPASH analysis. It continuously draws attention to important factors like "Working sector" and "Work at night shift", highlighting how strongly they correlate with the target variable, "Abuse". Figure 4 illustrates how these characteristics and others capture temporal dependencies. On the other hand, some features are not as significant as these well-known contributors.

Our study used a dataset that had not been subjected to machine learning analysis before, to investigate the main factors influencing child labor abuse. After a thorough analysis, we discovered previously undiscovered information about the factors that contribute to abuse. Interestingly, we found strong associations with the working sector, parental conditions, to abuse prevalence. Furthermore, our analysis showed age and gender differences in the incidence of abuse, with young males in Egypt's workforce between the ages of 5 and 11 being the most vulnerable.

5 Conclusion

In this study, we examined the prevalence and dynamics of child labor abuse within the Egyptian context using a combination of machine learning and explainable AI models. By analyzing various factors such as working sector, parental conditions, and night shift work, we aimed to identify key drivers of child labor abuse and predict potential cases. The experiments were conducted using a dataset collected from specific regions and sectors in Egypt. We employed machine learning techniques to analyze the data, focusing on both prediction accuracy and interpretability of the models. The use of explainable AI allowed us to understand the contribution of different factors to the prediction outcomes, providing valuable insights for stakeholders.

However, this research has several limitations. The dataset's geographic and sectoral limitations may restrict the generalizability of our findings to other regions or sectors. Additionally, the selected features might not encompass all relevant factors influencing child labor abuse, and potential biases in data collection could affect the model's accuracy and fairness.

Future research should address these limitations by incorporating more complex models and a broader range of socioeconomic and cultural variables. Expanding the study to include data from multiple countries can enhance the understanding of how different environments impact child labor abuse, leading to globally applicable intervention strategies. Developing real-time monitoring and intervention systems using advanced machine learning models could significantly improve the prevention and response to child labor abuse. Finally, ensuring ethical and responsible AI development is crucial, with a focus on fairness, accountability, and transparency to avoid inadvertent harm and bias.

Acknowledgments

ChatGPT and Grammarly were used for improving the structure and refining language. The use of AI tools was limited to enhancing clarity and coherence, and no content was directly copied or generated by these tools.

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