A COMPREHENSIVE SURVEY AND ANALYSIS OF MACHINE LEARNING TECHNIQUES FOR EARLY DETECTION OF CHILD BEHAVIORAL AND EMOTIONAL CHALLENGES

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Abstract

Maternal Mental health plays an important role in early childhood and emotional development. Increasing maternal employment in India, connected with lack of family and husband support, leads rise maternal stress, affecting children's internalizing and externalizing behaviors. Traditional predictive models often struggle to understand the complexity, non-linear interactions of family dynamics, requiring the transition toward advanced machine learning. This survey reviews present literature differentiating between pattern focused and prediction focused ML models used to identify early signs of emotional and behavioral issues. Methods such as Random Forest, XGBoost have been applied to predict child behavioral outcomes, but gaps remain in studies focusing on Indian school six to twelve aged children. Addressing these factors enhances the early identification of vulnerable children and implementing the evidence-based interventions for mothers and children.

Keywords : Maternal Mental Health, Maternal Stress, Family Support, Child Behavioral Outcomes, Internalizing Behavior, Externalizing Behavior, Random Forest, XGBoost, CatBoost.

I. INTRODUCTION

Maternal emotional and psychological well-being contributes significantly to child behavioral development. Stress, anxiety and other stress indicators significantly influences a child internalizing and externalizing symptoms in behavior. A better maternal background that fostering and minimizing behavioral problems or difficulties. One of the other factors of maternal stress is employment. The quality of job, stability, working hours are also influence maternal well-being, which also affect children's emotional and mental behavior [1,2,3]. In India, female labour participation is 43.2%(MOSPI,2025), depicting the growing participation of women in the occupational sector. While workforce participation provides a financial freedom, professional and personal growth, it also increases the burden on working mothers, who often manage occupational and family responsibilities. This also reason for maternal stress, depression and anxiety. A study points out that family support, especially from spouse and other family members, plays a significant role in promoting maternal functional recovery and psychological well – being [4]. Strong emotional, practical and social support from spouse and family members can reduces the maternal stress and promote a nurturing parenting practices. However insufficient support from family and spouse leads to work-family conflict and adversely affect the quality of parent child relationship. These dynamic changes in the family environment destroy the behavioural, emotional as well as mental health of a child [5]. Thereby combined effects of maternal mental health, maternal employment and family support have a significant role in identifying children at behavioural and emotional risk.

While previous researches have depicted the importance of maternal mental health, family support and maternal employment influencing child behavioural and emotional growth. These showcase the gap, in most cases the study conducted on infant or the perinatal period and early childhood, with comparatively less attention given to school aged children six-twelve. Furthermore, many studies have reported that maternal stress, family support, maternal employment with child outcome independently than exploring their combined influence. In addition to most of previous studies are conducted statistical approach and a few in machines learning techniques using independent parameters. At present there is a lack of survey that systematically reviews the machine learning approaches for early identification of behavioural and emotional problems in children. Considering these gaps may support the development of more accurate predictive model and promote timely, evidence-based interventions for both mother and child.

This survey reviews how machine learning approaches can help to identify the emotional and behavioural risk in children. Also, this paper focuses and analysis the commonly used datasets, parameter selections, evaluation matrices and framework for prediction in the previous studies. By connecting all these facts this paper aims to bring a clear

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understanding of how the maternal stress and mental health affect the child behavioural and emotional development.

A. Maternal Mental Health and Child Outcomes

Maternal mental health, including emotional and psychological health plays a significant role in child emotional and behavioural development [6]. Children of mothers affected mental stress and low mental health exhibits internalizing behaviours (such as withdrawal, anxiety, and low self-esteem) and externalizing behaviours (such as aggression, hyperactivity, and defiance).To predict child behaviour using the past studies showcases that both maternal and parental mental health has a significant outcome in child development [7].

In addition to the relationship among child and mother is based on physical and psychological health as well as infant behaviour and sleep quality[8].To detect depression on gender based a multi model data set is also used to capture the key patterns of demographic differences[9].Many of the studies focus on peripartum or infancy rather than school aged children and that there is substantial heterogeneity in the design, dataset quality and choice of ML methods pointing to the need for unified analytical frameworks and standardization evaluation procedures[10]

B. Family and Husband Support

Family and support from spouse are significant factors that mitigate maternal stress and create positive child outcomes. When child care and household activities shared among, this reduces mother maternal stress and mental well-being that helps in reducing the behavioural and emotional problems in children.

Incorporating family dynamics into risk prediction models can provide a extensive understanding of children's developmental risk, fostering early identification of children at risk and promoting timely interventions [11]. Mental and emotional support from the husband strengthen maternal well-being as well as children's psychological resilience. One of recent study on predicting air pollution by analysing various environmental factors using machine learning, this this approach can also be applied in to predict the child behaviour by family support factors [12].

C. Maternal Employment Stress

Maternal employment can lead additional challenges to mothers, including high job demands, long working hours, work pressure and work culture and tight deadline. Managing professional and house hold with child care is tedious task [13,14]. In India, a steady rise in women is entering the workforce, with the Female Labour Participation 43.2% [15]. Meanwhile employment provides financial independence and professional achievement; it may create additional challenges for mothers such as long working hours and high job demands, work place pressure and tight deadlines. Balancing professional responsibilities with childcare and household duties.

Such stressors can influence maternal mental health, leading anxiety, depression and fatigue, which in turn affect children's emotional and behavioural development. One of the analysis found that mothers who are joined in insecure job arrangements (such as contracts or economic inactivity) showcase a grater behavioural difficulty than children whose mothers were permanently employed [16]. Moreover, the studies evidences that from other domains deep learning in health care and parental employment quality affecting child outcomes [17]. Most studies have looked at how machine learning can predict behavioural risks in infants; there is a considerable lack of bridging school aged children (six-twelve years).

This gap underscores the need for identifying the emotional and behavioural challenges faced by this age group. Addressing this gap can help to understand at-risk children early and promote timely interventions that truly benefit their emotional and behavioural well-being.

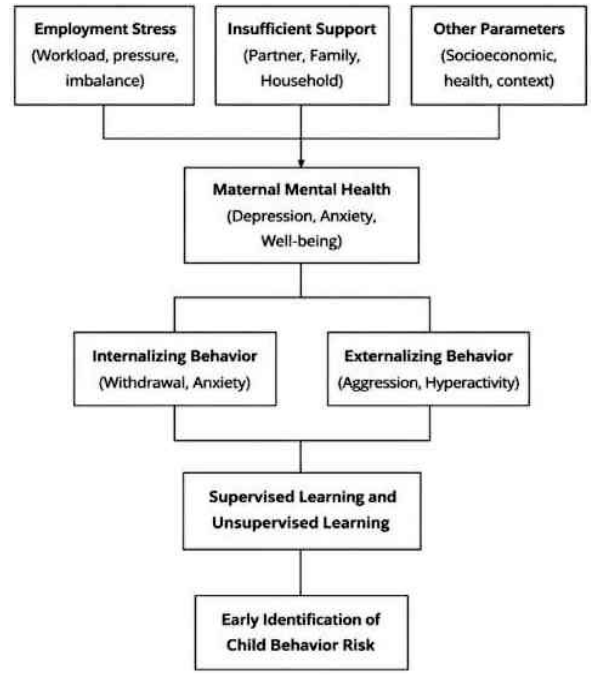

Fig. 1. Maternal well-being and its impact on child behavioural development

II. LITERATURE SURVEY

In this paper [1], researcher collected maternal mental health and demographic data, carried out feature engineering and preprocessing, trained multiple tabular machine learning models including LightGBM, XGBoost, CatBoost, Random Forest, and SVM, and predicted infant negative emotionality

during the first postpartum year.

In this [2] study, the author collected maternal stress, child behavioural, sibling, and demographic data, applied generalized linear models and cross-lagged panel analysis, and evaluated the relationship between maternal stress, older siblings, and children's behavioural outcomes.

This paper [3], the researcher obtained multiple scientific databases, performed a systematic review and meta-analysis, and examined the association between maternal employment characteristics and child's mental health

In this research [4], the author retrieves postnatal functional status, social support, and anxiety data, performed statistical analysis, end evaluated the relationship between maternal functional recovery, social support, and anxiety.

In this [5] study, the data collected using maternal stress, shared reading, and child behavioural data, performed regression and moderation analyses, and evaluated internalizing and externalizing behavioural outcomes in children.

This paper [6], the author collected longitudinal maternal and paternal perinatal depression, anxiety, and infant developmental data, applied longitudinal statistical analysis, and examined their association with infant developmental outcomes.

The present study [7], the authors collected, pregnancy, new-born, and early-life risk factor data, pre-processed the dataset, trained a CatBoost Regression model and predicted emotional and behavioural difficulties in children at five years of age.

In this study [8], the researchers obtained maternal and infant health data, performed clustering and feature extraction, trained Random Forest and Multi-Layer Perception models, and predicted infant behavioural characteristics and sleep quality.

This paper [9], collected multimodal depression datasets, applied uncertainty-based feature learning techniques, trained the U-Fair multitask learning model, and performed fair and accurate depression detection.

This article [10], analysed multiple scientific databases, screened and evaluated eligible studies, analysed machine learning techniques including ensemble algorithms, artificial neural networks (ANN), and Bayesian Kernel Machine Regression (BKMR), and identified maternal peripartum risk factors associated with adverse child development outcomes.

In this study [11], the authors collected maternal work–life balance, perceived stress, parenting practices, and child social adjustment data, performed mediation analysis, and examined the indirect effects of maternal stress and parenting practices on children's social adjustment.

In this study [12], retrieve clinical liver disease data, applied SHAP-based feature interpretation, trained a hybrid ensemble model incorporating XGBoost and performed the early detection and staging of liver cirrhosis. This method can be also to implement the analysis of mother and child relationship.

This paper [13], gives a longitudinal maternal employment and child behavioural data, performed regression analysis, and evaluated the association between insecure maternal employment and children's behavioural difficulties.

In this study [14], the author obtained air quality and environmental data, pre-processed dataset, trained machine learning models, and predicted air.

This article [15], MOSPI (2025) collected national labour force data and reported trends in female labour force participation across India through the Periodic Labour Force Survey.

This research [16], In this study, the authors reviewed deep learning-based pneumonia detection methods, analyzed convolutional neural network (CNN) architectures, and evaluated their performance in medical image classification.

In this study [17], the authors collected longitudinal parental employment quality, child mental health, and academic performance data, applied statistical modeling techniques, and evaluated the impact of employment quality on children's mental health and school performance.

III. PROPOSED SYSTEM

Most previous studies have focused on single or limited number of factors, to evaluate the child behavioural outcomes such as maternal stress, depression, anxiety, family support or employment. The proposed system address these drawbacks and by combining multiple parameters such as maternal, familial, employment and child- related data to evaluate the factors affecting maternal stress.

This enables a comprehensive and accurate early prediction and assessment of child behavioural and emotional risks among school aged children.

The study took the input variable as maternal factors as stress, depression, anxiety, emotional ell-being, age, and education. The family factors include husband support, family support, family structure and socioeconomic status. To analyse the employment status of a mother, the factors are employment status, employment quality, working hours and job security. To understand the child outcome these are the variable included age, gender, behavioural assessment.

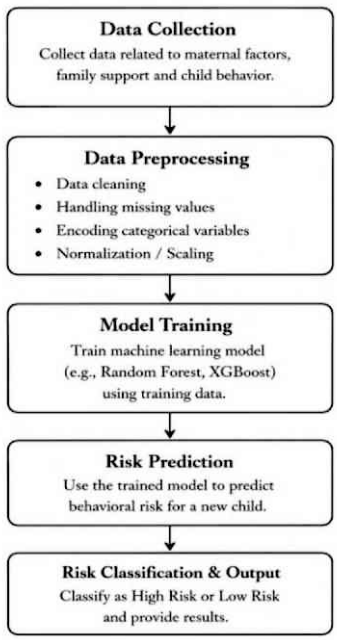

Fig.2. Different stages of child behavioural prediction model

For this assessment there are various stages data collection,

- Data cleaning
- Missing value handling
- Feature scaling
- Feature selection

Methodologies

- Random Forest
- XGBoost
- CatBoost

Machine Learning for Prediction Algorithms Model-Mediated Stacked Ensembles:

A. Random Forest (RF):

Random Forest is a corner stone for behavioural prediction due to its ability to handle imbalanced data and perform effective feature selection. Studies have reported accuracies ranging from 88% in mental health diagnosis to 95% in predicting cognitive outcomes based on maternal risk factors. Combining RF with MLP has proven

Particularly effective in modelling the relationship between maternal health and child characteristics

$$y=\text{mode}\{T_1(x),T_2(x),\ldots\ldots,T_n(x)\} \quad (1)$$

Where :

x=[x1,x2,x3,…….xm] is the feature vector,

x1=Maternal Stress,

x2=Maternal Mental Health,

x3= Family support,

x4=Husband support

Ti(x) = prediction of the i-th decision tree in the forest (At-Risk = 1, Not At-Risk = 0)

n = total number of trees in the forest

y = final predicted class determined by majority vote of all trees

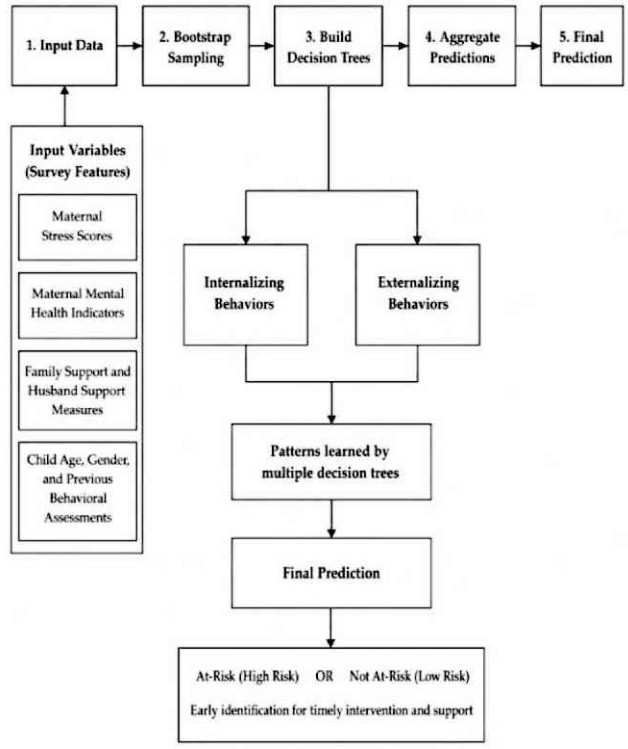

Fig.3. Random Forest Workflow for Predicting At-Risk Children Based on Maternal Stress, Family Support, and Child Behavioral Outcomes.

B. CatBoost (Gradient Boost):

CatBoost ideal for survey-based and categorical data. They can capture non-linear relationships and handle multicollinearity between variables, making them highly suitable for complex datasets.

- **Prepare the Data** – Load the dataset and identify numerical and categorical features.
- **Train Sequential Trees** – Build decision trees one after another, where each tree learns from the errors of the previous trees.
- **Update Predictions** – Combine the output of each new tree with previous predictions to reduce errors.
- **Generate Final Prediction** – Aggregate all trees' outputs to produce the final prediction and evaluate the model.

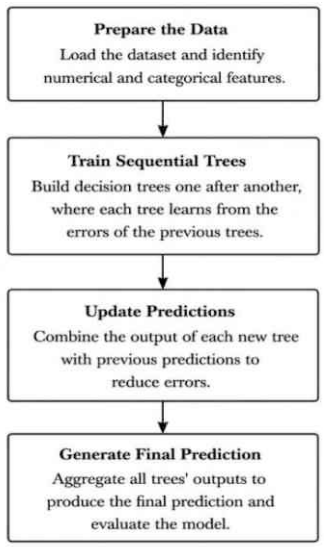

Fig.4. Simplified CatBoost Pipeline for Predicting Child Behavioral Risks from Maternal Stress and Family Support

C. XGBoost (Extreme Gradient Boosting) Algorithm:

This algorithm builds a collaborative learning model on decision trees sequentially. Each tree corrects the mistakes of previous trees, it effective for solve complex relationships and imbalanced datasets.

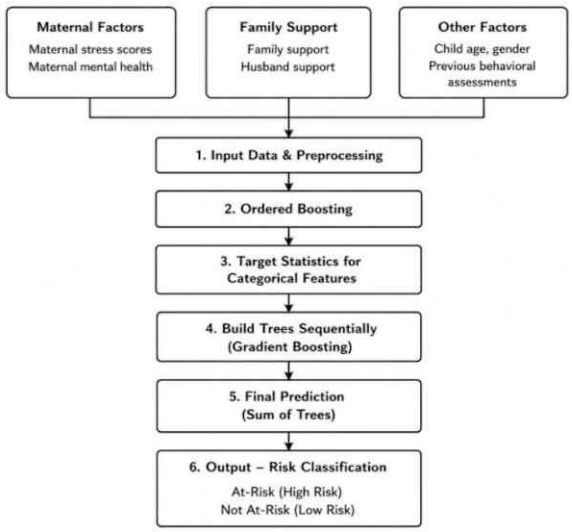

Fig.5. XG Boost-Based Risk Prediction for Child Behavioral Outcomes.

- **Input Data**: Maternal stress scores, mental health indicators, family and husband support, child demographics.
- **Preprocessing**: Handle missing values and encode categorical variables.
- **Sequential Tree Building**: Trees are built one after another; each new tree focuses on correcting previous errors.
- **Aggregation of Predictions**: Weighted predictions from all trees are combined.
- **Output**: Predicts whether a child is At-Risk or Not At-Risk for behavioral and emotional problems.
- **Interpretation**: Feature importance can show which maternal or family factors most affect child outcomes.

Future research should focus on developing interpretable machine learning models, utilizing larger longitudinal datasets, and incorporating diverse psychosocial and environmental factors to improve prediction accuracy and enhance the practical application of these models in maternal and child healthcare. Future research should focus on developing interpretable machine learning models, utilizing larger longitudinal datasets, and incorporating diverse psychosocial and environmental factors to improve prediction accuracy and enhance the practical application of these models in maternal and child healthcare. Future research should focus on developing interpretable machine learning models, utilizing larger longitudinal datasets, and incorporating diverse psychosocial and environmental factors to improve prediction accuracy and enhance the practical application of these models in maternal and child healthcare. Future research should focus on developing interpretable machine learning models, utilizing larger longitudinal datasets, and incorporating diverse psychosocial and environmental factors to improve prediction accuracy and enhance the practical application of these models in maternal and child healthcare.

IV. FINDINGS

For this survey Random Forest was selected as the main predictive algorithm because it is excellent to handle complex data with multiple factors such as maternal stress, mental health indicators, family support and child behavioral outcome. By integrating the predictions of many decision trees Random Forest works as reliable, flexible and suited to identify the relationship with multiple factors. Random Forest considered as advanced algorithm like XGBoost, CatBoost, TabFPN. These methods are effective at conducting study on non-linear data sets. It is also capable of handling categorical survey-based data and providing high predictive accuracy. By using this methods helps to accurately predict the children at-risk also un-covering the key factors of maternal and family factors. These data provide reliable evidence connecting maternal stress indicators to child behavioral outcomes. With all these reference Random Forest algorithm is a reliable and predictive to find the relation between mother and child relationship.

V. RESULT AND DISCUSSION

The findings from the previous studies illustrate a strong relationship between maternal mental health and child's behavioural and emotional development. There a different factor that influence the maternal stress, anxiety and depression. Several studies reported that higher levels of maternal stress were associated with increased psychological and emotional problems. Studies that incorporated a broader range of maternal, familial, and child-related variables generally provided more comprehensive risk assessments than those relying on a single factor or a limited set of variables.

The studies also indicated a growing interest in applying machine learning technique to maternal and child health research. Among the algorithms reported ensemble learning methods such as Random Forest, XGBoost, CatBoost, and LightGBM were frequently used because the of their ability to handle the complex datasets and capture nonlinear relationship among multiple risk factors.

Future research should focus on developing interpretable machine learning models, utilizing larger longitudinal datasets, and incorporating diverse psychosocial and environmental factors to improve prediction accuracy and enhance the practical application of these models in maternal and child healthcare.

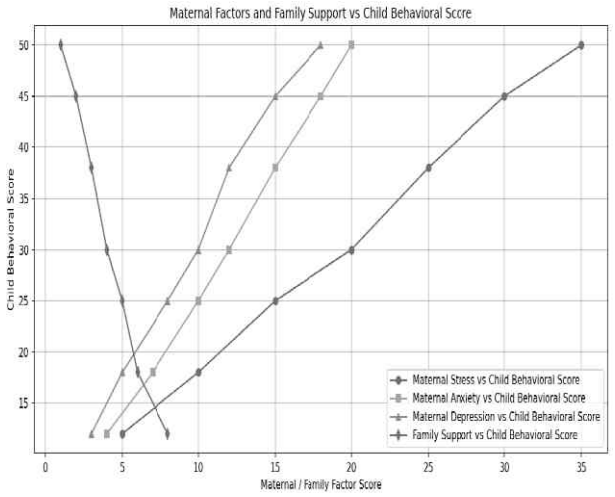

Fig.6. Reflection on Child behavioural issues based on maternal stress parameters.

VI. CONCLUSION

Machine Learning approaches offer promising tools for early identification of at-risk children, allowing timely interventions. Integrating maternal stress, mental health, and family support improves predictive accuracy. High-impact ML offers a scalable framework for identifying at-risk children before behavioral problems escalate. The algorithms such as Random Forest, CatBoost, XGBoost have showcases that the high performance in predicting behavioral changes in children. Future research must address the geographic gap in India and the age gap for children six-twelve years. Practically, these findings advocate for workplace wellness policies and interventions focused on shared reading to protect the developmental foundations of the next generation.

REFERENCES

[1] R. AlSaad, M. Alabdulla, A. Tabassum, J. Sheikh, and R. Thomas, “From mother to infant: Predicting infant temperament using maternal mental health measures and tabular machine learning models,” Front. Public Health, vol. 13, Art. 1659987, 2025.

[2] F. Amici, A. O. Wertz, T. Hieronymus, et al., “Maternal stress, child behavior and the promotive role of older siblings,” BMC Public Health, vol. 22, Art. 863, 2022.

[3] M. Kopp, M. Lindauer, and S. Garthus-Niegel, “Association between maternal employment and the child´s mental health: A systematic review with meta-analysis,” Eur. Child Adolesc. Psychiatry, vol. 33, pp. 3025–3042, 2024.

[4] N. Chandra and M. V. Smitha, "Functional status, social support, and anxiety among postnatal women of Eastern India," European Journal of Obstetrics & Gynecology and Reproductive Biology: X, vol. 20, Art. no. 100238, 2023, doi: 10.1016/j.eurox.2023.100238.

[5] C. R. Kroeff, J. R. Bernardi, C. H. Da Silva, N. C. Valentini, M. Z. Goldani, and D. R. Bandeira, “Maternal stress and child development: The moderating role of interactive shared reading,” Int. J. Environ. Res. Public Health, vol. 22, Art. 916, 2025.

[6] A. M. Rogers, G. J. Youssef, S. Teague, M. Sunderland, G. Le Bas, J. A. Macdonald, R. P. Mattick, S. Allsop, E. J. Elliott, C. A. Olsson, and D. Hutchinson, “Association of maternal and paternal perinatal depression and anxiety with infant development: A longitudinal study,” J. Affect. Disord., vol. 338, pp. 278–288, 2023.

[7] X. Zong, Y. Li, C. Liu, and E. Aguirre, “Predicting children's emotional and behavioral difficulties at age five using pregnancy and newborn risk factors: Evidence from the UK Household Longitudinal Study,” J. Affect. Disord., vol. 385, Art. 119336, 2025. doi: 10.1016/j.jad.2025.04.167.

[8] Z. Yang, X. Guo, X. Chen, and J. Huang, “Modeling the relationship between maternal health and infant behavioral characteristics based on machine learning,” PLoS ONE, vol. 19, no. 8, Art. e0307332, 2024. doi: 10.1371/journal.pone.0307332.

[9] J. Cheong, A. Bangar, S. Kalkan, and H. Gunes, “U-Fair: Uncertainty-based multimodal multitask learning for

fairer depression detection," in Proc. 4th Machine Learning for Health Symposium, in Proc. Mach. Learn. Res., vol. 259, pp. 203–218, 2025.

[10] H.-F. Tu, L. Zierow, M. Lennartsson, and S. Schweitzer, "A scoping review and quality assessment of machine learning techniques in identifying maternal risk factors during the peripartum phase for adverse child development," PLoS One, vol. 20, no. 5, Art. e0321268, 2025. doi: 10.1371/journal.pone.0321268.

[11] R. Hosokawa and T. Katsura, "Maternal work–life balance and children's social adjustment: The mediating role of perceived stress and parenting practices," Int. J. Environ. Res. Public Health, vol. 18, no. 13, Art. 6924, 2021.

[12] Dr.M.M.Karthikeyan, "A SHAP-Enhanced Hybrid Stacked Ensemble Model Using XGBoost for Early Detection and Staging of Liver Cirrhosis", IEEE Xplore, September-2025.

[13] M. Li and Y. Chzhen, "Insecure maternal employment and children's behaviour difficulties: Evidence from the longitudinal study of Australian children," Soc. Sci. Med., vol. 354, Art. 117077, 2024. doi: 10.1016/j.socscimed.2024.117077.

[14] Sivaraman, M., & Shriman, B. (2026, May). Air Pollution Level Prediction using Machine Learning. In 2025 3rd International Conference on Sustainable Computing and Smart Systems (ICSCSS). IEEE.

[15] Ministry of Statistics and Programme Implementation (MOSPI), Periodic Labour Force Survey (PLFS) 2023–24: Annual Report, Government of India, 2025. [Online]. Available: https://mospi.gov.in/plfs

[16] K.Kathirvel, Javahar S. Deep Learning Techniques for Pneumonia Detection: A Review of CNN Applications, In Proceedings of the 9th International Conference on Electronics Communication and Aerospace Technology ICECA 2025. IEEE.

[17] A. E. Fuller, F. V. Shahidi, J. Comeau, L. Wang, G. Wahi, J. Dunn, C. S. Birken, A. Siddiqi, and K. Georgiades, "Parental employment quality and the mental health and school performance of children and youth," J. Epidemiol. Community Health, vol. 79, no. 8, pp. 552–558, 2025.