# Women Remote Health Status Prediction System for Pregnant

G.Srimyndhan[1], Santhosh.C[2]
[1]*M.Sc Data Science and business analysis,* [2]*Assistant professor*
[12]*Rathinam collage of arts and science*

**Abstract - Insufficient real-time remote monitoring options for expectant mothers impede the prompt identification of possible health issues, resulting in less than ideal outcomes for both the mother and the fetus. Continuous monitoring outside of clinical settings is a problem for the healthcare systems already in place, particularly in distant places. A novel and intuitive wearable gadget, smartphone application, and predictive analytics-integrated remote health status prediction system is desperately needed. By anticipating and averting probable pregnancy issues, this approach seeks to improve the proactive management of maternal health and, consequently, the overall health outcomes for expectant mothers. While identifying and treating signs of anxiety and depression in pregnant women is crucial, there are still many obstacles to overcome. Specifically designed to track mental health indicators in perinatal women, this research presents a novel hybrid data management platform powered by artificial intelligence (AI). To assess several datasets pertaining to symptoms of anxiety and depression, the study uses Naive Bayes, k-Nearest Neighbors (KNN), and Support Vector Machines (SVM). Based on the combineddata, the SVM algorithm is used to identify trends and categorize different degrees of anxiety and sadness. By utilizing proximity-based learning, KNN enhances this, while Naive Bayes improves predictions by taking into account the probabilistic correlations between symptoms. These days, computers can accurately diagnose a wide range of medical diseases since large healthcare datasets are readily available and machine learning techniques have advanced.Finding the most compelling questions about anxiety and sadness in two pregnant males by extracting features using performance-optimized algorithms is the main goal of the study.**

## I. INTRODUCTION

The increasing importance of digital data in a variety of domains, such as research, technology, society, and healthcare, is what defines the big data era [10]. These datasets make it challenging to swiftly extract meaningful data from the full study, which severely limits processing power and the analytics framework. In order to address these kinds of problems, research into creating a productive big data analytics platform is required [6]. Many research studies have been heavily incorporated into the creation of big data analytics frameworks, such as Apache Spark, Apache Hadoop, Apache Storm, and Apache Kafka, in order to solve healthcare challenges. Because mental health disorders have a significant impact on people's lives, they are important health issues that need to be managed carefully [2]. If mental disorders that appear during the perinatal period which includes the pregnancy process are not identified and treated in a timely manner, both the mother and the fetus will suffer. If accurate, this has a big effect on the mental health of society. Machine learning has the power to direct the creation of new disease models, preventative measures for mental health disorders, and innovative medications. The solution is provided by machine learning algorithms that analyze data on the big data analytics platform[1]. It provides support for the investigation and development of new medications to treat illnesses in the field of medicine. To mitigate the effects of this period, researchers and psychiatrists have an extraordinary opportunity to use machine learning techniques to harness intricate patterns in the brain, behavior, and disease.Studies show that the global incidence of perinatal depression is between 10% and 20%, while the prevalence of prenatal anxiety disorders is between 10% and 24%. A history of anxiety or depressive disorders was found to be the best predictor in previous investigations. Taking into account all of these and related studies, a patient's evaluation takes longer due to the huge number of risk variables. Additionally, when the study is carried out, a sizable client base will be contacted and a sizable quantity of data will be gathered. These factors make a big data platform necessary to speed up the procedure, ease the burden on expectant mothers, and enable analysis. Therefore, the goal is to reduce the possible harm that anxiety and depression can do to pregnant women. This problem has been examined in our study, and outcomes that will improve the outcome have been attained [11]. Results for the solution are revealed by machine learning algorithms that are utilized on the big data analytics platform to make sense of data. It promises to provide insight into the identification and creation of novel remedies for illness. Methods employed in the identification of brain and mental illnesses have produced inaccurate or partial images, with insufficient outcomes. It is critical for the advancement of big data analytics in the field of psychology to positively impact mental health issues. It is evident that there are times in life when psychological disorders health issues that have a profound impact on people's lives and require cautious treatment are more prone to arise. One of these processes is the perinatal phase, which encompasses the pregnancy process. Researchers and psychiatrists have an unparalleled opportunity to employ machine learning approaches to leverage complex patterns in the brain, behavior, and disease in order to lessen the harm caused by this era.

The "Feature Selection" approach was used since it was thought to be suitable for all data.After this point, artificial intelligence approaches were used to develop a model that yields the outcome with an appropriate level of sensitivity. The model's excellent accuracy performance was evaluated for randomness using the 10-Fold cross-validation technique. The big data platform was equipped with the machine learning algorithm that outperformed all of these artificial intelligence techniques. As a result, a method that can quickly diagnose illness has been created. One of the features of this system is that it can act as a platform for more substantial data infrastructure. This big data platform can help replace the laborious process of identifying anxiety and sadness in expectant mothers with computer-based tools that function quite accurately and in real time.

## 1.1 Objectives:

The main goal is to create a system that can identify the early warning indicators and symptoms of anxiety and depression in the prenatal stage. This is known as early detection and intervention. Early detection is critical for successful intervention and support.

Precise Symptom Evaluation: Develop artificial intelligence systems that can precisely determine the degree of phobic and depressed symptoms based on a range of data, including behavioral indicators, physiological data, and self-reports [4].

Customize the monitoring and evaluation procedure for every individual, accounting for their unique needs, characteristics, and potential hazards.

Establish a system that can promptly alert patients or medical experts when concerning symptoms are discovered. These alerts should be actionable, necessitating support or a reaction.

Integration with Healthcare Systems: Make the platform compatible with existing healthcare systems and electronic health records to facilitate easy communication and teamwork among medical experts.

When creating the platform, scalability should be taken into account so that it may be expanded to serve larger populations and modified to meet changing healthcare requirements.

Cost-Effectiveness: It is important to consider the platform's cost-effectiveness to ensure that both patients and healthcare providers benefit from it.

Education and knowledge: Educational materials should be developed and public knowledge of the site's benefits should be raised in order to encourage perinatal patients and medical professionals to use the platform [3].

## 1.2 Methodology:

1.2.1. Determine the Issue: Clearly state the issue you want to solve. In this instance, the requirement for a remote monitoring system to forecast and oversee the health condition of expectant mothers may apply.
1.2.2.Describe the Goal: Clearly define what the system's goal is. One goal might be to create a dependable and easy-to-use platform that remotely tracks and forecasts pregnant women's health, improving the early identification of possible issues.
1.2.3. Describe the Purpose: Indicate the system's reach. Think of things like the variety of health metrics that need to be tracked, the target population (women who are expecting), and the areas where the system will be implemented.
1.2.4. Determine the Stakeholders: Determine the important parties pregnant women, medical professionals, and system administrators.
1.2.5. Think about Ethical Issues: Recognize and discuss moral issues such informed consent, data protection, and the appropriate application of predictive analytics in healthcare.
1.2.6. Describe the Success Criteria: Clearly state the standards by which the system's success will be judged. This could involve elements like forecast accuracy, user happiness, and a smooth interaction with current healthcare workflows.
1.2.7. Expect Difficulties: Determine any dangers and difficulties that might arise during the system's development and implementation. This could involve unforeseen legal obstacles, problems with user acceptability, or technological difficulties.
1.2.8. Forecast for Health Status: Make use of machine learning algorithms to forecast a person's state of health by analyzing past data and present health indicators. Incorporate variables like mother age, gestational age, and past medical history into the prediction model.

1.2.9. Warning System: Install an alert system to inform consumers and healthcare practitioners of any anomalies or possible health dangers. Establish cutoff points for several health metrics, setting off alarms when figures depart markedly from the average.
1.2.10. Interface User: Provide a user-friendly interface so that medical professionals and expectant mothers may both access and understand the health data. Incorporate patterns and infographics to give users a long-term understanding of their health status [5].
1.2.11. Privacy and Security: Put strong security measures in place to guarantee the privacy and accuracy of the medical data. Respect privacy laws and get users' informed consent before collecting and analyzing their data.
1.2.12. Remote Observation: Provide a scalable and safe cloud architecture to gather and store the information from
mobile apps and wearable devices. Make sure that health data is periodically or in real-time transmitted to the cloud.
1.2.13. Channels of Communication: Provide safe means of communication so that medical personnel can communicate with expectant mothers from a distance. For consultations, offer video conferencing or messaging services.
1.2.14. Comments and Instruction: Based on their health information, provide pregnant women with tailored feedback. Supply instructive materials via the platform to encourage pregnancy-safe practices [7].
1.2.15. The ability to grow and evolve: Create a scalable system to handle an increasing number of users. As new technologies become available, include them into your plan for future improvements.
1.2.16. Importance: The Increase the early identification of pregnancy-related health issues. Facilitate prompt action to improve outcomes for both mothers and fetuses. Enable remote access to healthcare, especially in underprivileged or isolated regions. Give healthcare professionals insightful information so they can deliver individualized care.

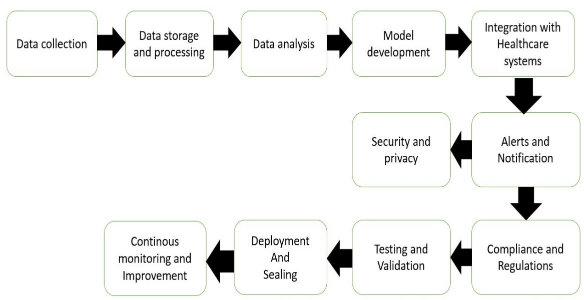


Figure: 2.1

Monitoring the Mental Health states

2. Literature survey:
2.1 Predicting health condition by using a machine learning model based on Spark streaming large amounts of data:
This project investigates the application of Spark-based machine learning models on streaming big data to predict health statuses. Using Apache Spark's capabilities for efficient processing of large-scale streaming data, the researchers aim to develop a predictive model that can analyze health-related data in real-time, enabling swift and accurate predictions. The integration of Spark's distributed computing framework ensures scalability and performance, which is crucial for handling the velocity and volume of streaming health data [20].

2.2 Review of advancements and difficulties in perinatal mental health:
This research explores prenatal mental health in great detail, looking at both the field's advancements and problems. The research, which was carried out by L. M. Howard and H. Khalifeh, is discussed in relation to a review that was published in October 2020 in World Psychiatry. Perinatal mental health is evaluated critically in this study, which covers the time from pregnancy to the first year after giving birth. The authors emphasize developments in comprehending and treating prenatal mental health concerns by a thorough analysis of the body of past research. They explore the various facets of perinatal mental health, such as prevalence, risk factors, and effects on the health of the mother and child.
The initiative highlights the ongoing difficulties in providing prenatal mental health care by pointing out gaps in current understanding and practices. The writers talk on social stigmas, obstacles to successful intervention, and the need for better screening and support networks. The study also looks at possible directions for further

investigation and legislative efforts to improve the results for perinatal mental health [12].

2.3 Using deep learning to identify depression among Twitter users:
This study investigates the use of deep learning methods to identify depression in Twitter users. A. H. Orabi, P. Buddhitha, M. H. Orabi, and D. Inkpen's research, which was presented in the 5th Workshop on Computational Linguistics and Clinical Psychology Proceedings, examines the developing relationship between social media and mental health.

In order to find potential signs of sadness, the study focuses on using deep learning models to examine the linguistic patterns and material provided by Twitter users. The authors employ state-of-the-art techniques for natural language processing and machine learning to convey their findings from a thorough analysis of tweets. The study explores the methods used to train and validate the deep learning model, focusing on the subtleties of depression detection in a text-based online environment. The research has implications for the possible creation of automated solutions for social media platform early mental health issue diagnosis and intervention. This study advances the rapidly developing field of clinical psychology computational linguistics by demonstrating the effectiveness of deep learning in identifying mental health trends in the digital discourse of social media [15].

3. Model development :

This study aims to determine the characteristics that have the greatest impact on anxiety and depression symptoms in pregnant women, along with other pertinent aspects, in order to identify the disease with less information Figure 3.1. The acquired data are then real-time processing on the big data platform and interpreted using the artificial intelligence module. In this context, a variety of studies have been conducted, as can be observed when we review the literature. Pregnant women are therefore among the demographic groups most susceptible to mental health issues during this time [9]. This study is the first to use the questions from the dataset developed by specialists in medicine to diagnose these patients. After a thorough review of several electronic scientific sources, it was discovered that the published papers did not adequately examine two pregnant men for anxiety and depression using machine learning on the big data platform with this dataset [16]. At specific second intervals throughout the sixth stage, Apache Spark, the Consumer, receives all of the data that has been cleaned and prepared using feature selection methods from Kafka Producer. At the seventh stage, the Streaming API enabled the Utilize Apache Spark as the consumer to receive the stream in a fault-tolerant, highly effective manner. The best-performing Naive Bayes algorithm then engaged with the incoming data through the Apache Spark MLLIBAPI, and the disease results were output. A thorough Remote Health Monitoring System (RHMS) for expectant mothers is the suggested remedy. Predictive analytics, a mobile application, a secure cloud-based infrastructure, and wearable gadgets are all included in this solution. It is intended to deliver tailored health insights, early diagnosis of issues, and real-time monitoring for expectant mothers and medical professionals. Using the Naive Bayes algorithm, we were able to get an accuracy rate of 90.80% when examining depression and anxiety in perinatal women. It may be concluded that the method developed is this rate is fairly high, making it appropriate for usage in the field of mental health. In order to predict sadness and anxiety, the second method uses machine learning techniques including Random Forest, SVM, Naive Bayes, K-Nearest Neighbors (K-NN), C-Nearest Neighbors, and Spark features. The third method used the big data processing platform to apply the best machine learning algorithm to all the data after it had been prepared and cleaned using feature selection methods [8].

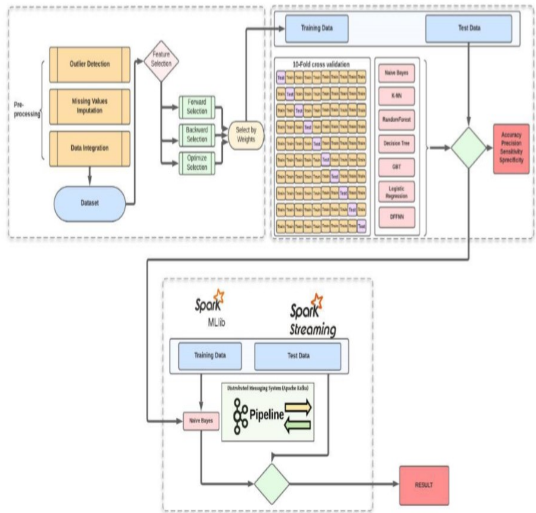


Figure: 3.1
An overview of the suggested architecture for data analytics.

The RHMS's user interface, which includes trend analysis tools and graphics for simple health data interpretation, is made for intuitive interaction. The implementation of an alarm system that can be customized for different health parameters alerts users and healthcare providers about potential hazards or deviations from normal values. Additionally, the system incorporates secure communication channels within the mobile application, enabling video conferencing and messaging features to enable remote consultations between expectant mothers and medical specialists. The suggested implementation plan calls for developing collaborations with healthcare providers, designing the mobile application, extensively testing wearable technology, and running a pilot program to get input from users. The system will be scaled in accordance with the pilot's performance, with ongoing assessment and monitoring conducted in accordance with predetermined success criteria, such as user happiness, forecast accuracy, and adherence to ethical norms. Essentially, the RHMS offers a proactive, customized, and easily available approach to mother health, with the goal of revolutionizing prenatal care. The Naive Bayes model was trained and tested using 80% of the patient dataset. Twenty percent of the dataset produced streaming data that this model interacted with. Incoming test data, the instantaneous classification of the data by the naive Bayes algorithm, and the anticipated outcomes based on the data training model are all shown in Figure 3.2.

3.1. Strategy of Implementation: To guarantee accuracy and user comfort, wearable technology should undergo extensive testing. Create a functional prototype of the mobile application and receive input from the intended audience. For cooperation and integration into current healthcare systems, form alliances with healthcare providers. Utilizing a variety of datasets, implement and test the predictive analytics model [17]. Launch the system in a test phase, keeping an eye on user input and adjusting as needed. Expand the user base and work with more healthcare organizations to scale the system in response to the pilot's success.

3.2. Observation and Assessment: Evaluate the system's performance on a regular basis in relation to predetermined success criteria, such as user satisfaction, prediction accuracy, and ethical standards compliance. Get input from healthcare professionals and users alike to determine what needs to be optimized and improved. The Remote Health Monitoring System for Pregnant Women seeks to transform prenatal care by introducing this technology and offering a proactive and customized approach to maternal health.

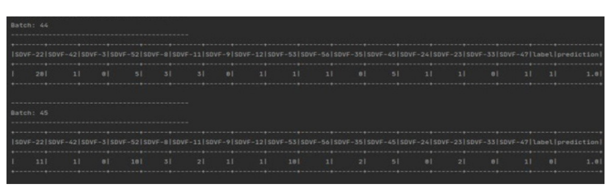

Figure: 3.2
Naive Bayes anticipated the streaming outcome.

To quantify the error of a test run on a machine learning model more precisely, a technique known as cross validation is applied during model selection. Using a 10-fold cross-validation process, we separated the model's training and test data for our analysis. Ten equal parts of the data set are extracted using the 10-fold cross-validation process. One of the remaining nine components serves as the test dataset, and the other nine components make up the training dataset. This technique is repeated ten times until every component is a test data set. Using the accuracy values as a mean, the model's correctness is ascertained. A major obstacle is the lack of efficient, real-time remote monitoring options for expectant mothers, which can result in delayed identification of possible health issues and less than ideal outcomes for both the mother and the fetus. Traditional healthcare systems find it difficult to offer continuous monitoring outside of clinical settings, especially in geographically remote places. A feature-rich Remote Health Monitoring System (RHMS) is suggested as a solution to this problem. Predictive analytics, wearable technology, a mobile app, and a secure cloud-based infrastructure are all integrated into one system to deliver real-time monitoring, early complication diagnosis, and individualized health insights for expectant mothers and medical professionals. The RHMS solution consists of wearables that can monitor vital signs like blood pressure, weight, activity level, and heart rate [19]. These devices are made to be accurate and comfortable to wear. These wearables easily connect with a user-friendly mobile application, giving expectant mothers instant access to health information. With features like medication reminders, tailored health insights, and instructional materials, the mobile app equips users with knowledge about safe pregnant practices. The technology creates a strong cloud-based architecture to guarantee data security and adherence to healthcare laws. This infrastructure, which includes strict security controls and encryption standards, makes it easier to store and handle health data securely. Machine learning algorithms power predictive analytics, which examines both past and current health data to create a model for early pattern recognition and possible difficulties. This allows for the prompt warning of users and healthcare practitioners. Table 3.1 displays the evaluation metrics for Apache Spark's Naive Bayes algorithm.

| Parameter | value |
|---|---|
| Accuracy | 92.45% |
| Precision | 97.29% |
| Sensitivity | 92.30% |
| F1 | 92.60% |

Table: 3.1
Parameters of the Naive Bayes model are assessed.

4. Experimental results:

Self-administered questionnaires were used to collect clinical factors for the creation of datasets in this investigation. The PASS scales, SDVF, and EPDS are examples of clinical variables. This dataset looks into patients' diagnoses of anxiety, depression, or both. The purpose of this research is to reduce the possible negative effects of anxiety and depression in women. The categories of classification and streaming results are used to group the study's findings.

Naive Bayes has determined that the cross-validation of applying machine learning to the chosen with 90.80% accuracy, 86.90% sensitivity, 92.34% specificity, 81.71% precision, and 0.966 AUC, Optimize Selection has yielded the best results. Then, using the most effective machine learning algorithm Naive Bayes the machine learning model was trained on the vast data processing platform. The streaming results section also includes the outcomes from this platform [18].

In the earlier phases, the best feature selection algorithm was used to preprocess and prepare all patient data. At exactly one second, this data is pushed into Kafka Broker by Kafka Producer. The Kafka Consumer retrieves the data for use in its assigned tasks upon being pushed into the Kafka Broker by the Kafka Producer. The Spark engine is linked to the Kafka Consumers. The pace at which data arrive is combined (from all sources) by the input rate. The process rate indicates the speed at which data is examined. The total number of records that a trigger has handled is displayed in the input rows. The batch duration shows how long each batch's processing took.

Conclusion:

In summary, a significant advancement in the use of technology to improve maternal care has been made with the creation and implementation of the remote mental health state prediction system for expectant mothers.

This system is positioned as a useful tool in managing mental health difficulties during pregnancy because to its successful integration of machine learning models, real-time monitoring using wearable devices, and user-friendly interfaces. The improvements in security protocols, alert system efficacy, and predictive model performance highlight the potential influence on early intervention and support for expectant mothers. Moving forward, maintaining the system's relevance and efficacy will require constant monitoring, iterative enhancements, and engagement with healthcare experts. People will experience various situations in their life that will be detrimental to their psychological equilibrium. During the prenatal period is one of the most important times for mental wellness. It is a given that if proper care is not given at this critical era, the mother, the child, and society's mental health would all suffer grave consequences. There isn't a study attempting to treat women as rapidly using a hybrid big data analytics platform, but it is undeniable that a system that makes it easier and faster for patients to receive diagnosis and treatment is necessary in such a significant industry. Particular attention is paid to hybrid big data platforms in this study that identify mental health disorders through machine learning methods. The information that has the greatest bearing on the dataset's outcome was chosen using feature selection algorithms in an effort to reduce the amount of forms and scales that women have to fill out and to identify pregnant women who were at a higher risk of developing anxiety or depression at an earlier age. Optimal, sequential forward (SFS), and sequential backward (SBS) feature selection techniques

. It has been noted that the approach with the best performance is the optimal selection method that makes use of genetic algorithms. The effectiveness and usefulness of six distinctThe Decision Tree, Naive Bayes, K-NN, Random Forest, GBT, Logistic Regression, and DFFNN machine learning classifiers were evaluated. The ML parameters were optimized with the use of cross validation. Six evaluation procedures were employed to corroborate the results: accuracy, sensitivity, specificity, and precision. The testing data were registered. With 90.80% accuracy, the Naive Bayes Classifier with the selected features performed the best, according to the results.It is easy to conclude that the model we built can be utilized efficiently for diagnosis because of its high accuracy rate.

REFERENCES


[1] N.B.Oğur,M.Al-Hubaishi,andC.Çeken,''IoTdata analytics architecture for smart healthcare using RFID and WSN,'' ETRI J., vol. 44, no. 1, pp.135–146,Feb.2022,doi:10.4218/ETRIJ.2020-0036.

[2] "Detection of postnatal depression: Development of the 10-item Edinburgh postnatal depression scale," by J. L. Cox, J. M. Holden, and R. Sagovsky British Journal of Psychiatry, volume 150, issue 6, June 1987, pp. 782–786, doi: 10.1192/BJP.150.6.782.

[3] The article "A review of feature selection methods in medical applications" by B. Remeseiro and V. Bolon-Canedo can be found in Computer Science and Medicine, vol. 112, Sep. 2019, art. no. 103375, doi: 10.1016/J.COMPBIOMED.2019.103375.

[4] G.Zini, "Artificial intelligence in hematology," Hematology, 10.1080/10245330410001727055, vol. 10, no. 5, pp. 393–400, Oct. 2005

[5] Expert Syst. Appl., vol. 32, no. 4, pp. 1084–1093, May 2007, doi: 10.1016/J.ESWA.2006.02.005, A. Subasi, "EEG signal classification using wavelet feature extraction and a mixture of expert model."

[6] Machine learning to predict clinical remission in depressed patients after acute phase selective serotonin reuptake inhibitor treatment, S. Zhou, Q. Ma, Y. Lou, X.Lv, H. Tian, J. Wei, K. Zhang, G. Zhu, Q. Chen, T. Si, G. Wang, X. Wang, N. Zhang, Y. Huang, Q. Liu, and X. Yu, J. Affect. Disorders, vol. 287, pp. 372–379, May 2021, doi: 10.1016/J.JAD.2021.03.079.

[7] In their paper "On the feature selection for battery state of health estimation based on charging–discharging profiles," Y. Li, D.-I. Stroe, Y. Cheng, H. Sheng, X. Sui, and R. Teodorescu The article "102122" appears in J. Energy Storage, vol. 33, January 2021, doi: 10.1016/j.est.2020.102122.

[8] IoT data analytics architecture for smart healthcare employing RFID and WSN, N.B. Oğur, M. Al-Hubaishi, and C. Çeken, ETRI J., vol. 44, no. 1, pp. 135–146, Feb. 2022, doi: 10.4218/ETRIJ.2020-0036.

[9] In their work "Perinatal generalized anxiety disorder: Assessment and treatment," S. Misri, J. Abizadeh, S. Sanders, and E. Swift Journal of Women's Health, vol. 24, no. 9, September 2015, pp. 762–770, doi: 10.1089/JWH.2014.5150.

[10] In their comprehensive review, "Anxiety disorders during pregnancy," J. H. Goodman, K. L. Chenausky, and M. P. Freeman October 2014; J. Clin. Psychiatry, vol. 75, no. 10, p. 1177; doi: 10.4088/JCP.14R09035.

[11] C.Nagarajan and M.Madheswaran - 'Experimental verification and stability state space analysis of CLL-T Series Parallel Resonant Converter' - Journal of ELECTRICAL ENGINEERING, Vol.63 (6), pp.365-372, Dec.2012.

[12] C.Nagarajan and M.Madheswaran - 'Performance Analysis of LCL-T Resonant Converter with Fuzzy/PID Using State Space Analysis'- Springer, Electrical Engineering, Vol.93 (3), pp.167-178, September 2011.

[13] C.Nagarajan and M.Madheswaran - 'Stability Analysis of Series Parallel Resonant Converter with Fuzzy Logic Controller Using State Space Techniques'- Taylor & Francis, Electric Power Components and Systems, Vol.39 (8), pp.780-793, May 2011.

[14] C.Nagarajan and M.Madheswaran - 'Experimental Study and steady state stability analysis of CLL-T Series Parallel Resonant Converter with Fuzzy controller using State Space Analysis'- Iranian Journal of Electrical & Electronic Engineering, Vol.8 (3), pp.259-267, September 2012.

[15] Nagarajan C., Neelakrishnan G., Akila P., Fathima U., Sneha S. "Performance Analysis and Implementation of 89C51 Controller Based Solar Tracking System with Boost Converter" Journal of VLSI Design Tools & Technology. 2022; 12(2): 34–41p.

[16] C. Nagarajan, G.Neelakrishnan, R. Janani, S.Maithili, G. Ramya "Investigation on Fault Analysis for Power Transformers Using Adaptive Differential Relay" Asian Journal of Electrical Science, Vol.11 No.1, pp: 1-8, 2022.

[17] G.Neelakrishnan, K.Anandhakumar, A.Prathap, S.Prakash "Performance Estimation of cascaded h-bridge MLI for HEV using SVPWM" Suraj Punj Journal for Multidisciplinary Research, 2021, Volume 11, Issue 4, pp:750-756

[18] G.Neelakrishnan, S.N.Pruthika, P.T.Shalini, S.Soniya, "Perfromance Investigation of T-Source Inverter fed with Solar Cell" Suraj Punj Journal for Multidisciplinary Research, 2021, Volume 11, Issue 4, pp:744-749

[19] C.Nagarajan and M.Madheswaran, "Analysis and Simulation of LCL Series Resonant Full Bridge Converter Using PWM Technique with Load Independent Operation" has been presented in ICTES'08, a IEEE / IET International Conference organized by M.G.R.University, Chennai.Vol.no.1, pp.190-195, Dec.2007

[20] M Suganthi, N Ramesh, “Treatment of water using natural zeolite as membrane filter”, Journal of Environmental Protection and Ecology, Volume 23, Issue 2, pp: 520-530,2022
[21] M Suganthi, N Ramesh, CT Sivakumar, K Vidhya, “Physiochemical Analysis of Ground Water used for Domestic needs in the Area of Perundurai in Erode District”, International Research Journal of Multidisciplinary Technovation, pp: 630-635, 2019
[22] P. C. Austin, J. V. Tu, J. E. Ho, D. Levy, and D. S. Lee, ‘‘Using methods from the data-mining and machine-learning literature for disease classificationandprediction:Acasestudyexaminingclassificationofheartfailure subtypes,’’J.Clin.Epidemiol.,vol.66,no.4,pp. 398–407,Apr.2013,doi: 10.1016/J.JCLINEPI.2012.11.008.
[23] L. M. Howard and H. Khalifeh, ‘‘Perinatal mental health: A review of progress and challenges,’’ World Psychiatry, vol. 19, no. 3, pp. 313–327, Oct. 2020, doi: 10.1002/WPS.20769.
[24] B. Remeseiro and V. Bolon-Canedo, ‘‘A review of feature selection methods in medical applications,’’ Comput. Biol. Med., vol. 112, Sep. 2019, Art. no. 103375, doi: 10.1016/J.COMPBIOMED.2019.103375.
[25] P. C. Austin, J. V. Tu, J. E. Ho, D. Levy, and D. S. Lee, ‘‘Using methods from the data-mining and machine-learning literature for disease classification and prediction: A case study examining classification of heart failuresubtypes,’’J.Clin.Epidemiol.,vol.66,no.4,pp.398–407,Apr.2013,doi:10.1016/J.JCLINEPI.2012.11.008.
[26] A. H. Orabi, P. Buddhitha, M. H. Orabi, and D. Inkpen,‘‘Deep learning for depression detection of Twitterusers,’’in Proc.5thWorkshop Comput. Linguistics Clin. Psychol., From Keyboard Clinic, 2018, pp. 88–97.
[27] H. Cao, A. Meyer-Lindenberg, and E. Schwarz, ‘‘Comparative evaluation of machine learning strategies for analyzing big data in psychiatry,’’Int. J. Mol.Sci.,vol.19,no.11,p.3387,Oct.2018,doi:10.3390/IJMS19113387.
[28] S. Misri, J. Abizadeh, S. Sanders, and E. Swift, ‘‘Perinatal generalized anxiety disorder: Assessment and treatment,’’ J. Women’s Health, vol. 24, no. 9, pp. 762–770, Sep. 2015, doi: 10.1089/JWH.2014.5150.
[29] D. Hubbeling, ‘‘Overtreatment: Is a solution possible?’’ J. Eval. Clin. Pract., vol. 28, no. 5, pp. 821–827, Oct. 2022, doi: 10.1111/jep.13632.
[30] A. Sau and I. Bhakta, ‘‘Screening of anxiety and depression among the seafarers using machine learning technology,’’ Informat. Med. Unlocked, vol. 16, Jan. 2019, Art. no. 100149, doi: 10.1016/J.IMU.2018.12.004.
[31] L. R. Nair, S. D. Shetty, and S. D. Shetty, ‘‘Applying spark based machine learning model on streaming big data for health status prediction,’’ Comput. Electr. Eng., vol. 65, pp. 393–399, Jan. 2018, doi: 10.1016/j.compeleceng.2017.03.009.