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Review on Vitamin D Deficiency and Role of Machine Learning.

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ABSTRACT
Vitamin D deficiency is a widespread health problem with a variety of consequences for human health. It has severe influence on several body organs. Having sufficient amount of Vitamin d helps to reduce many several complications in the human body. People with insufficient Vitamin D are at higher risks of infections and other diseases. Incorporating recent trends of technologies can help to understand and study the different approaches in this field. Machine Learning plays important role in predicting the severity levels of Vitamin D deficiency by using its data analytic capabilities for large datasets identifying the patterns that are not immediately apparent to human researchers. This study aims to provide valuable insights into the potential of machine learning in enhancing the prediction of Vitamin D deficiency severity.

Keywords—Vitamin D Deficiency , Machine Learning

1. Introduction

Vitamin D is fundamental for general wellbeing and sickness counteraction, as indicated by ongoing examinations. A few types of malignant growth, provocative sicknesses, and bone irregularities have all been related to vitamin D inadequacy. Notwithstanding these notable issues, a few more are presently being explored. The way that vitamin D is a fat-solvent nutrient ought to assist with clearing things up. The skin creates most of its vitamin D requirements when presented to daylight — around 90%. Traditional ways to deal with distinguishing and treating this shortfall frequently have their restrictions. Consequently, to instantly mediate and give treatment options, it is significant to analyze the level of vitamin D inadequacy precisely. The utilization of AI to examine enormous datasets to pinpoint those most in danger of deficiency, nonetheless, has shown empowering results. AI based expectation frameworks can possibly precisely recognize instances of vitamin D inadequacy in individuals. Accordingly, the motivation behind this exploration is to give light on how AI might work on the conclusion and treatment of vitamin D inadequacy.

Natural Sources of Vitamin D :

The body's metabolic cycles, when presented to daylight, make vitamin D underneath the skin, making it the essential wellspring of vitamin D.

SOURCES	FOODS
Meat Source of Vitamin D	Beaf Liver
Plant Source of Vitamin D	Mushrooms
Dairy Source of Vitamin D	Egg Yolks, Cheese
Protein Rich Source of Vitamin D	Fatty Fish and Fish Lever Oil
Added Source of Vitamin D	Fortified Foods & Vitamin D Supplements

Vitamin D Deficiency Statistics across the Globe

With side effects going from gentle to serious, vitamin D inadequacy influences an expected one billion people universally.

Key References	Region-wise Variations	Vitamin D Deficiency Percentage
Holick, M. F[22]	Middle East and South Asia	80% to 90%
Chakhtoura, M. Rahme[23]	Europe	20% to 60%
	North America	40%
International Osteoporosis Foundation [24]	Australia and New Zealand	30%

II. Existing Review Analysis

Study/Method	Key Findings	Limitations/Gaps
Enhanced Random Forest Classifier	Achieved 91.42% accuracy for predicting vitamin D insufficiency based on environmental and dietary parameters.	Lack of investigation into hereditary variables; underemphasis on supplementation.
Decision Tree Approach	96% success rate in estimating severity of vitamin D insufficiency; identified related risk factors.	Ignored geographical and seasonal influences; need for more sensitive models.
Comparative Study of ML Approaches	Random Forest outperformed SVM, ENOR, and OLR in multiple metrics (accuracy, specificity, etc.).	Multicollinearity affects SVM efficiency; small sample sizes limit model effectiveness.
VitaDNet (Deep Learning)	Introduced a deep learning network integrating anthropogenic and dietary data; enhanced reliability in severity analysis.	Need for noninvasive detection methods; challenges with sex, pathology, and medical records.
NHANES 2001–2018 Analysis	XGBoost model highly effective in predicting vitamin D insufficiency using age, race, and BMI.	No techniques currently to estimate risk; focused on demographic factors only.
Machine Learning for Severity Prediction	Random Forest outperformed other classifiers with 96% accuracy; highlighted effectiveness in severity prediction.	Limited discussion on study constraints; little attention to extraneous variables.
Hypertensive Population Analysis	SVM was superior in detecting vitamin D insufficiency in hypertensive patients,	Lack of comparison to conventional diagnostic methods; limited discussion

	particularly in sensitivity.	on model restrictions.

Analyzing the performance using various evaluation parameter.

Many health issues may be brought on by a lack of vitamin D. Determine which people have the lowest vitamin D tolerance

deficit played a urgent part. The shortfall of forecast devices adversely affects society all in all. In the cutting edge age, AI calculations might decrease the probability of lacks of nutrient by means of examination.

Author	Year	Method	Dataset	Metrics measured
Jiale guo et al. [26]	2024	GB, LR, RF, SVM, XG boost	**2. NHANES 2001-2018**	Accuracy-100%, PPV-99.9%, NPV-99.8%, Sensitivity-99.9%, Specificity-99.9%, F-score-99.8%,MCC-99.7, kappa-99.7%, Brier score-0.013
Shuyu Guo et al. [27]	2013	RBF SVM	Ausimmune Study dataset	PCC of 0.74
Alloubani et al. [28]	2023	Optimized RF	Collected data among 350 Saudi Arabia citizens	Accuracy-91.42%
Sluyter et al [29]	2022	LR, ENR, RF, GB, DT, DNN	Vitamin D assessment (ViDA) between 2011 and 2012	Accuracy, precision, recall
Saha et al. [30]	2023	LR and RF	Data collected from 50 SLE patients in Bangladesh	**LR:** RMSE- 4.83, MAE-3.86, **RF:** RMSE-2.98 and MAE-2.68

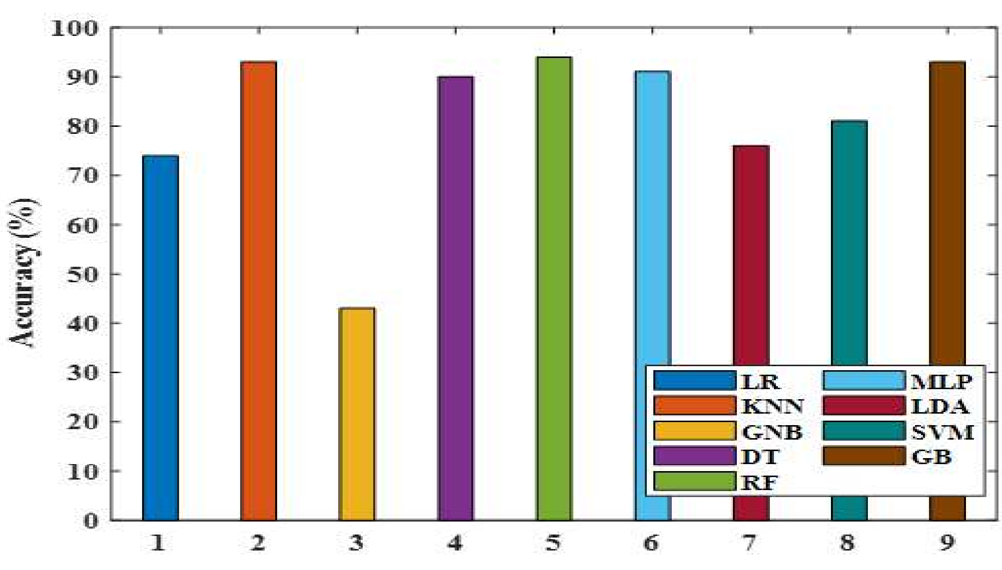

Figure 6 (a) :Performance analysis of ML models

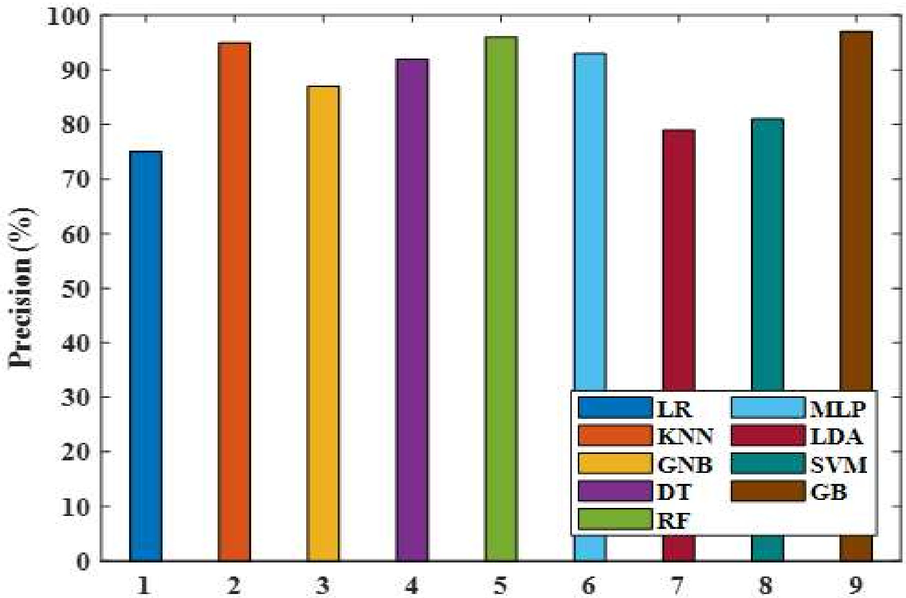

Figure 6 (b):Performance analysis of ML models

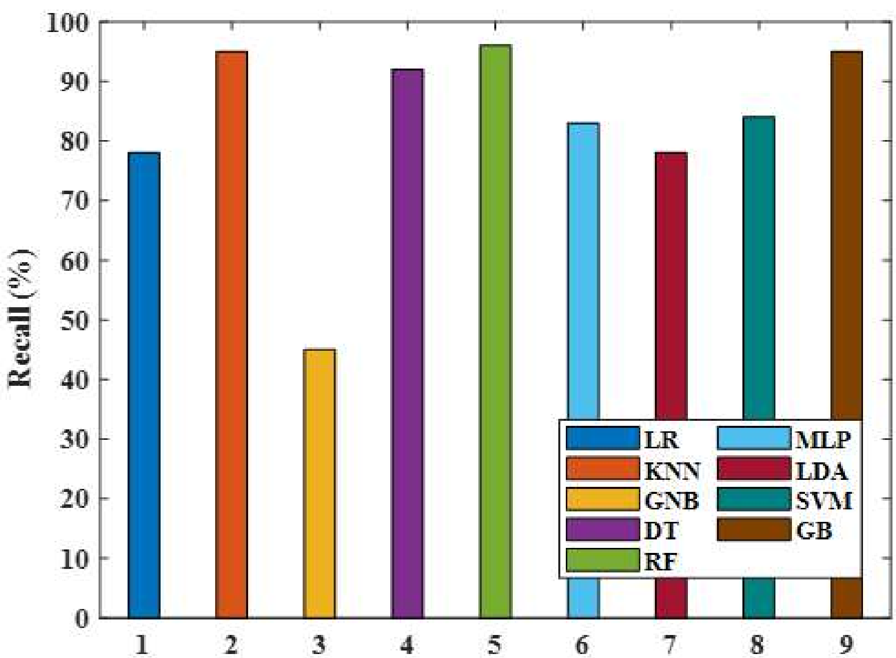

Figure 6 (c):Performance analysis of ML models

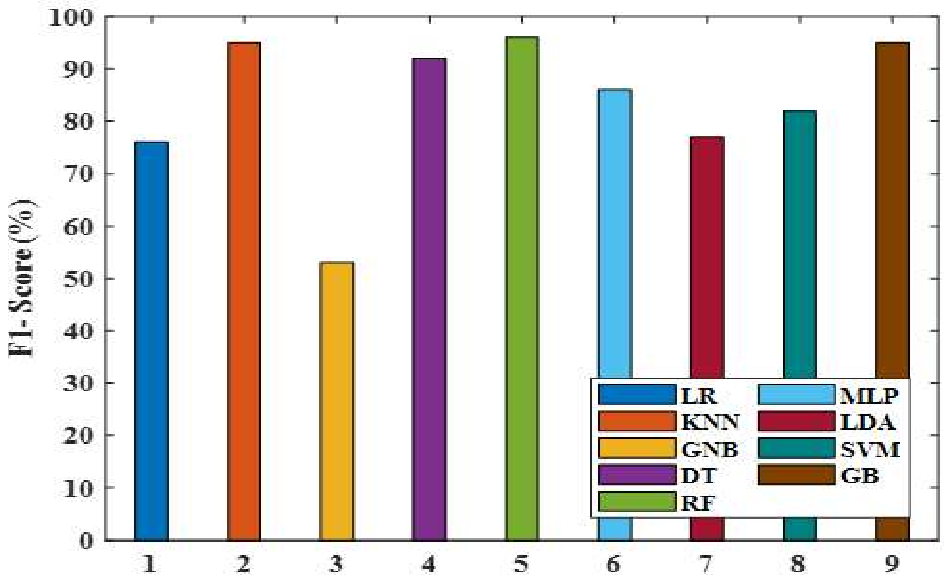

Figure 6 (d):Performance analysis of ML models

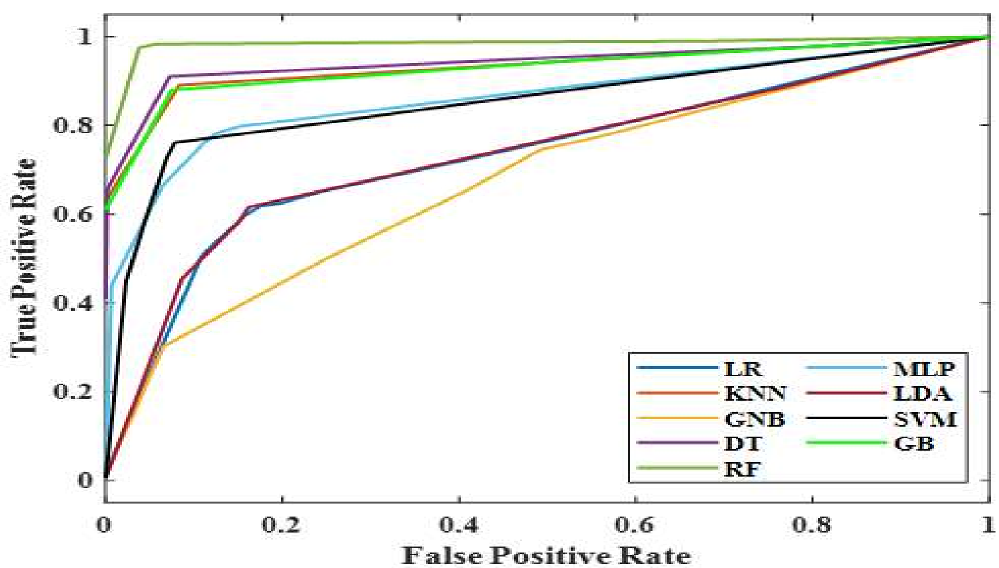

Figure 6 (e):Performance analysis of ML models

III Methodology and Approach

Dataset Arrangement and Improvement

Preprocessing and further improvement of the gained dataset follows the dataset assortment step and is a significant piece of the exploration approach. Preceding taking care of the data into the AI models, it is urgent to clean, standardize, and scale the elements to ensure it is predictable and of top caliber. Information expansion procedures, for example, picture flipping, zooming, and turn, may likewise help model generalizability and execution by growing the dataset. Besides, stresses the need of careful preprocessing and expansion in supporting the expectation execution of ML calculations by means of model power and sound decrease. Thusly, to boost the last model's anticipated precision and reliability, an exhaustive preprocessing and expansion system ought to be utilized [16].

We might adopt a calculated strategy to the issue of applying numerical ways to deal with extricate qualities and recognize conspicuous characteristics related with lack of vitamin D:

A. Feature Extraction

Bringing crude information into a model-accommodating configuration is what's really going on with include extraction. A few significant side effects of vitamin D inadequacy might include:

Instances of natural markers incorporate calcium levels, parathyroid chemical (PTH) levels, serum 25-hydroxyvitamin D levels, and others.

Age, orientation, race, area (in view of the impact of scope on daylight openness), and so on.

An individual's level of active work, how much time they spend outside, how much vitamin D they consume, whether they take supplements, and so on.

Clinical Foundation: Ailments that impact the body's capacity to ingest or process vitamin D, for example, renal sickness or malabsorption problems.

Head part examination (PCA) and other area explicit methodologies might be utilized to diminish dimensionality in highlight extraction strategies. These techniques then alter and produce significant elements from the data.[5]

B. Feature Selection

The following stage, after highlight extraction, is to figure out which qualities are generally applicable to the forecast of vitamin D inadequacy. A few numerical strategies might be utilized for this reason:

Examination of Connections: Find qualities that have major areas of strength for a with the reliant variable (like serum vitamin D levels, for instance).

Scoring the Significance of Elements: Figure out how significant highlights are by utilizing calculations like XGBoost or choice trees like Irregular Woods.

Ways to deal with Regularization: By punishing less significant characteristics, procedures like Rope relapse may actually pick the most pertinent ones [8].

Information Obtained: The prescient capability of every trademark might be shown by measurements like entropy or Gini file, which are particularly significant in choice tree-based approaches [7].

C. Dominant Feature Selection

With regards to anticipating vitamin D inadequacy, prevailing qualities are the ones that make the biggest difference. To pick unmistakable attributes:

Before utilizing highlight choice systems, rank elements as per their importance scores or significance scores.

Thresholding: Kill pointless highlights by laying out an end score for include importance or some other standard.

Ability: Utilize your subject aptitude to affirm the meaning of the predominant qualities.

iv. Workflow

Data Collection: Gather data from research or clinical records that relate to blood vitamin D levels, socioeconomics, way of life decisions, and clinical foundation.

Feature Extraction: Remake valuable attributes from crude information by utilizing significant factual methodologies and subject mastery.

Feature Selection: To figure out which numerical factors are generally prescient of vitamin D inadequacy, use strategies like connection investigation and component importance calculations.

Dominant Feature Identification: Utilize the attributes' appraisals or measurable importance to figure out which ones are generally significant.

Model Building: Utilize the picked ruling attributes to fabricate vitamin D inadequacy expectation models, (for example, choice trees or relapse models).

Validation: Confirm the model's strength and trustworthiness by utilizing appropriate approval strategies, like cross-approval.

By sticking to this purposefully coordinated system, we might work on the accuracy and understandability of vitamin D inadequacy forecast models by numerically separating and choosing ruling qualities.

Severity Level Identification and Classification

To precisely expect vitamin D inadequacy, it is important to initially foster a reasonable structure for characterizing and ordering seriousness levels. This requires gathering appropriate clinical information and physiological pointers, and afterward utilizing AI calculations to decide the level of the deficiency. Assuming you need your arrangement model to be precise and dependable, you want to preprocess and advance the dataset. A solid numerical model is fundamental for highlight extraction and element choice to further develop the calculation's expectation execution [20].In the end, we need to have a solid technique that can order vitamin D inadequacy into different seriousness levels so that individuals might get help rapidly. Researchers might decide the methodology's viability and reliability in clinical settings by testing the arrangement model and contrasting its outcomes with those of different methodologies.

Vitamin D status is typically classified based on serum 25(OH)D levels measured in ng/mL or nmol/L:

- ***Sufficiency***: Serum 25(OH)D levels ≥ 30 ng/mL (≥ 75 nmol/L)
- ***Insufficiency***: Serum 25(OH)D levels 20-29 ng/mL (50-74 nmol/L)
- ***Deficiency:***Serum 25(OH)D levels < 5 ng/mL (< 12.5 nmol/L)
- ***Mild***: Serum 25(OH)D levels 10-19 ng/mL (25-49 nmol/L)
- ***Moderate:*** Serum 25(OH)D levels 5-9 ng/mL (12.5-24 nmol/L)

Clinical Assessment and Interpretation

Notwithstanding blood levels, clinical assessment considers any side effects and other gamble factors that could exacerbate the shortage or better. Factors, for example, age, skin pigmentation, healthful utilization, sun openness propensities, and scope of home are remembered for this.

Diagnostic Criteria and Guidelines

Rules for deciding the seriousness of a shortage are given by rules gave by various wellbeing associations:

Institute of Medicine (IOM):

Sufficiency: ≥ 20 ng/mL (≥ 50 nmol/L)

Deficiency: < 12 ng/mL (< 30 nmol/L)

Management and Treatment

Supplementation and way of life changes are among the treatment choices that are directed by the seriousness level:

Vitamin D supplementation, either orally, is the typical treatment for gentle to direct inadequacy; the sum depends on the patient's particular requirements and the seriousness of their condition.

On the off chance that the inadequacy is extreme, the patient might have to take more drug or go through more escalated treatment, which might incorporate beginning with a high-portion routine and afterward step by step lessening the dose.

Example:

Most proposals characterize a patient as having moderate vitamin D inadequacy in the event that their blood 25(OH)D level is 8 ng/mL. To redo treatment, a clinical assessment would consider side effects (if present) and other gamble factors.

V. Future Research Directions

Addressing Potential Overfitting: We ought to ponder alternate ways of forestalling overfitting as the model functions admirably on preparing information yet ineffectively on test information. Among them, you might find regularization strategies, dropout layers, or a more changed set of preparing information.

Handling Class Imbalance: Techniques like Destroyed might be utilized to oversample the minority class in an uneven dataset, or the preparation model's class loads can be changed.

Model and Hyperparameter Tuning: You might mess with different hyperparameters, like learning rates, model geographies, and the sky is the limit from there. Once in a while, greater generalizability might be accomplished by utilizing a less mind boggling model or changing the hyperparameters.

Incorporation of Advanced Data Integration Techniques: By gathering data on clinical, hereditary, and way of life factors, we can all the more likely figure out the reasons for early pregnancy misfortune.

Utilization of Transfer Learning: Using models that have proactively been prepared on comparable errands might upgrade execution.

Exploration of Time Series Analysis: Research relating to pregnancies frequently follows a severe course of events. Potential worldly examples connected to early pregnancy misfortune may be uncovered by utilizing calculations that can dissect patterns and changes continuously clinical information across time.

Vi. Conclusion

Models created in this exploration plainly showed guarantee after an exhaustive expectation execution assessment of vitamin D deficiency seriousness utilizing AI procedures. Dataset pretreatment and upgrade empowered highlight extraction, which thusly further developed seriousness level recognizable proof and characterization. Utilizing a numerical model to recognize the main qualities, the AI calculations effectively anticipated the level of vitamin D inadequacy. Execution measure appraisal demonstrated that the recommended techniques worked, showing that they beat the cutting edge concerning anticipated exactness. All in all, this study shows the commitment of AI as an apparatus for medical services suppliers to all the more likely expect and treat vitamin D inadequacy, which thus works on quiet results.

References

1. Holick, M. F. (2007). Vitamin D deficiency. New England Journal of Medicine, 357(3), 266-281.
2. Cashman, K. D., Dowling, K. G., Škrabáková, Z., Gonzalez-Gross, M., Valtueña, J., De Henauw, S., ... & Kiely, M. (2016). Vitamin D deficiency in Europe: Pandemic? The American Journal of Clinical Nutrition, 103(4), 1033-1044.
3. Pludowski, P., Holick, M. F., Pilz, S., Wagner, C. L., Hollis, B. W., Grant, W. B., ... & Łukaszkiewicz, J. (2018). Vitamin D effects on musculoskeletal health, immunity, autoimmunity, cardiovascular disease, cancer, fertility, pregnancy, dementia and mortality—a review of recent evidence. Autoimmunity Reviews, 17(12), 1173-1186.
4. Genuer, R., Poggi, J. M., & Tuleau-Malot, C. (2010). Variable selection using random forests. Pattern Recognition Letters, 31(14), 2225-2236.
5. Guyon, I., & Elisseeff, A. (2003). An introduction to variable and feature selection. Journal of Machine Learning Research, 3, 1157-1182.
6. Wang, J., & Zuo, W. (2016). A new feature selection method based on random forest. Pattern Recognition Letters, 76, 15-22.
7. Chandrashekar, G., & Sahin, F. (2014). A survey on feature selection
methods. Computers & Electrical Engineering, 40(1), 16-28.
8. Tibshirani, R. (1996). Regression shrinkage and selection via the lasso.
Journal of theRoyal Statistical Society: Series B (Methodological), 58(1), 267-288.
9.Guyon, I., Weston, J., Barnhill, S., & Vapnik, V. (2002). Gene selection for cancer classification using support vector machines. Machine Learning, 46(1-3), 389-422.
10. Holick, M. F. (2007). Vitamin D deficiency. New England Journal of Medicine, 357(3), 266-281.
11. Cashman, K. D., Dowling, K. G., Škrabáková, Z., Gonzalez-Gross, M., Valtueña, J., De Henauw, S., ... & Kiely, M. (2016). Vitamin D deficiency in Europe: Pandemic? The American Journal of Clinical Nutrition, 103(4), 1033-1044.
12. Pludowski, P., Holick, M. F., Pilz, S., Wagner, C. L., Hollis, B. W., Grant, W. B., ... & Łukaszkiewicz, J. (2018). Vitamin D effects on musculoskeletal health, immunity, autoimmunity, cardiovascular disease, cancer, fertility, pregnancy, dementia and mortality—a review of recent evidence. Autoimmunity Reviews, 17(12), 1173-1186.
13.James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An Introduction to Statistical Learning: with Applications in R. Springer Science & Business Media.
14. Hastie, T., Tibshirani, R., & Friedman, J. (2009). The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer Science & Business Media.
15.Julia Fedotova, "Vitamin D Deficiency", BoD – Books on Demand, 2020-02-26
16.Dennis Douroumis, "Hot-Melt Extrusion", John Wiley & Sons, 2012-06-25
17. Sudipta Roy, Lalit Mohan Goyal, Mamta Mittal, "Advanced
Prognostic Predictive Modelling in Healthcare Data Analytics", Springer Nature, 2021-04-22
18.Ivo D. Dinov, "Data Science and Predictive AnalyticsSpringer, 2018-08-27
19.Vikrant Bhateja, Suresh Chandra Satapathy, Carlos M. Travieso-Gonzalez, T. Adilakshmi, "Smart Intelligent Computing and Applications, Vol1", SpringerNature, 2022-04-18

20.Deepak Kumar Jain, Li Zhang, Guangming Zhang, Piyush Shukla,

21."Adoption of Artificial Intelligence in Human and Clinical Genomics", Frontiers Media SA, 2023-09-08

22. Holick, M. F. (2013). "Vitamin D deficiency: what a pain it is." Mayo Clinic Proceedings, 88(12), 1374-1381.

23. International Osteoporosis Foundation. (2018). "Vitamin D deficiency and insufficiency."

24. Chakhtoura, M., Rahme, M., Chamoun, N., & Fuleihan, G. E. H.2018.

25. "Vitamin D in the Middle East and North Africa." 2019 Bone Reports, 8, 135-146.

26. de Oliveira, Vanessa Rabello Lovisi Sales, and Caroline Pereira Domingueti. "Association of vitamin D deficiency and type 1 diabetes mellitus: a systematic review and meta-analysis." International Journal of Diabetes in Developing Countries 38 (2018): 280-288.

27.Suryawanshi Ranjeet, Amol Kadam, "Enhancing Software Defect Projections Performance by Class Rebalancing", International Journal of Intelligent Systems and Applications in Engineering, Volume 12, Issue 12s, Pages 183 – 191, 2024

28.Kadam Amol, Shrivastava Anurag, Pawar Sonali K.,Patil Vinod H,Michaelson Jacob, Singh Ashish, "Calories Burned Prediction Using Machine Learning" Proceedings of International Conference on Contemporary Computing and Informatics, IC3I 2023, Pages 1712 - 1717

29.Kadam Amol, Vempaty, Lakshmi Namratha,Kumar Melam,Durga Prasnna, Patil Vinod H, "Tackling Climate Change with Artificial Intelligence" Proceedings of International Conference on Contemporary Computing and Informatics, IC3I 2023Pages 1704 - 1711

30.Amol K. Kadam, Dr. Konda Hari Krishna, Neeraj Varshney, A. Deepak, Hemant Singh Pokhariya, Dr. Sandip Kumar Hegde, Dr. Vinod H. Patil, "Design of Software Reliability Growth Model for Improving Accuracy in the Software Development Life Cycle (SDLC)" International Journal of Intelligent Systems and Applications in Engineering, 12(1s), pp. 38-50, 2024

31.Suryawanshi, R., Kadam, A., Anekar, D., Patil, V. "An Innovative Approach for Predicting Software Defects by Handling Class Imbalance Problem" International Journal on Recent and Innovation Trends in Computing and Communication, Volume 11, Issue 9, pp. 498-505,2023.

32.Kadam Amol, Patil Vinod, Mali Mohan, Shinde Sandip, Madkar Shankar, Patil Ajit, Talale Ajay "Evaluating Awareness and Impact of Government Schemes in India: A Comprehensive Study" Library Progress International, Volume 44, Issue 3, Pages 2184 – 2191, Jul-Dec 2024

33.Patil Vinod, Patil Jaydip, Kadam Amol, Patil Ajit, Mokashi Devdatta, Lonare Girish " AI-Driven Green Space Optimization for Sustainable Urban Parks: Enhancing Biodiversity and Resource Efficiency" Library Progress International, Volume 44, Issue 3, Pages 3412 – 3417 Jul-Dec 2024