A Multi-class Classification Approach for Anemia Level Prediction with Machine Learning Models

Maria Trigka*, Elias Dritsas†, and Phivos Mylonas*
*Department of Informatics and Computer Engineering,
University of West Attica, Egaleo, Athens, Greece
{mtrigka,mylonasf}@uniwa.gr
†Department of Electrical and Computer Engineering
University of Patras, Patras, Greece
dritsase@ceid.upatras.gr

***Abstract*—It is a common belief that Artificial Intelligence (AI) and Machine Learning (ML) provide researchers and medical experts with concepts, tools, and techniques to build intelligent systems able to analyze, process and detect hidden patterns, in order to turn data into actionable knowledge for personalized medicine and decision-making (e.g., disease prevention via associated risk prediction, treatment, etc.). The present study seeks an ML solution that will facilitate the recognition of anemia level by investigating the performance of two well-established strategies for multi-class classification tasks; the One-Vs-All (OVA) and One-Vs-One (OVO). Under the specific strategies, two well-known ML models were assumed, namely, Logistic Regression (LR) and Support Vector Machines (SVM). The validation of both strategies was carried out in a publicly available dataset by measuring the weighted average performance in all involved classes that capture the anemia levels; accuracy, precision, recall and Area Under the ROC curve (AUC) were captured and compared for the identification of the dominant model and strategy. After the experimental evaluation, the OVO strategy with the LR model is the main suggestion of the current study achieving an accuracy of 95.05%, precision and recall equal to 0.951 and an AUC of 0.990.**

***Index Terms*—Anemia, Multi-class Classification, Prediction, Machine Learning, Data Analysis**

I. Introduction

Anemia is the condition in which there is a significant deficiency of viable red blood cells that carry oxygen from the lungs to the tissues, as well as carbon dioxide to the lungs for removal through exhalation [1]. There are several types of anemia, some hereditary and some acquired. The most common form of anemia worldwide for both genders and all age groups is iron deficiency anemia [2]. Additionally, other forms of anemia are hemolytic anemia, sickle cell anemia, megaloblastic anemia, pernicious anemia, mediterranean anemia, hemolytic anemia, aplastic anemia, and anemia due to bone marrow disorders [3].

Some causes that contribute to the appearance of anemia are the lack of iron and folic acid, the lack of vitamins, infections or inflammations, various diseases (chronic kidney disease, liver problems or spleen dysfunction), pregnancy, bleeding, bowel disorders (Crohn's disease and celiac disease), heavy menstruation and heredity [4]–[6].

Symptoms of anemia vary depending on its type and severity. The most common, however, are fatigue, irregular pulse, chest pain, paleness, shortness of breath, headache, dizziness or even frozen extremities. More severe types of anemia can cause fainting, severe dizziness and thirst, sweating, cramps and difficulty breathing. Other symptoms may be dark stools, blood in the urine or stools. Finally, burning or numbness in the hands is a symptom of anemia that can be linked to a lack of vitamin B12 [7], [8].

A blood test may be all that is needed if it is obvious what is causing the anemia. This will check the levels of iron, vitamin B12 and folic acid, the level of hemoglobin in the blood, how many blood cells there are, as well as their size and shape. If there is no obvious cause, additional tests such as a myelogram or some imaging method may need to be done [9], [10].

Treatment for anemia depends on the cause, but also on the intensity and type of symptoms. Most of the time, a healthy diet combined with nutritional supplements depending on the element missing from the body is sufficient to balance the issue. In more critical situations, a blood transfusion may be needed to compensate for the lack of red blood cells [11]. In addition, complications can occur if the anemia is severe and if not treated properly it can worsen an existing heart problem such as angina or heart failure [12].

A proper diet, which is rich in nutrients, is extremely important in treating anemia. Foods rich in iron combined with foods with vitamin C are very important for its intake and absorption by the body. Foods rich in iron are liver, red meat and poultry, eggs, green vegetables, nuts, the legumes, dark green leafy vegetables (e.g. spinach), dried fruit, cereals, bread and pasta with added iron [13], [14].

It is important to carry out regular laboratory testing in infants and children when there is a family history, as any alarming symptom should not be left uninvestigated, and there should be regular contact with the attending physician and specialist nutritionist [15].

Nowadays, AI and ML have transformed and revolutionized the way the healthcare sector operates helping institutions, practitioners, specialists and medical experts efficiently store, process and analyse big medical data to identify early signs of diseases, often more accurately than human doctors and at a lower cost. Supervised ML algorithms have been established as important tools in forecasting various chronic condition risk

prediction, such as breast cancer tumour type [16], chronic kidney disease [17], diabetes type-2 as classification [18], [19] or time-series tasks for continuous glucose prediction [20], [21], cardiovascular diseases [22]–[24], hypertension [25], [26], SARS-CoV-2 [27], mental confusion [28], lung cancer [29], sleep disorders [30], [31], liver disease [32] metabolic syndrome [33], [34], stroke [35], cholesterol [36], [37] etc.

The main motivation of this study was to present a multi-class classification framework for anemia level prediction that could support medical experts during the screening process of anemia since its occurrence may impact other co-existed conditions. For this purpose, we investigated the performance of two strategies (OVA and OVO) assuming LR and SVM as base models for solving the single binary classification tasks involved in each strategy [38]–[40] targeting a solution that can achieve high sensitivity and separation ability (namely, high recall and AUC). Exploiting a publicly available dataset, the LR classifier under the OVO strategy achieved more consistent outcomes in all classes and in general superior performance than the rest.

The remaining paper is structured as follows. Section II describes related works with the subject under study. Next, in Sections III and IV, a dataset description and analysis of the adopted methodology are described. Besides, in Section V, we discuss the acquired research results. Finally, conclusions and future directions are outlined in Section VI.

II. Related Works

In this section, we illustrate some relevant works with the study under investigation.

Firstly, [41] focused on the recognition of anemia under general clinical practice conditions. For this purpose, the authors experimented with four different ML models namely, Artificial Neural Networks (ANN), SVM, Naïve Bayes (NB), and Ensemble Decision Trees, and evaluated with various metrics. Also, the models utilized eight different datasets created via particular feature selection techniques. The highest accuracy (85.6%) was achieved using Bagged Decision Trees, followed by Boosted Trees (83.0%) and ANN (79.6%).

Moreover, in [42], the authors aimed to design a model to predict anemia in children under five years of age using complete blood count (CBC) reports. The data were normalized and balanced. Also, feature selection was applied. The RF model showed the biggest accuracy of 98.4%.

In paper [43], five ensemble ML methods namely, Stacking, Bagging, Voting, Adaboost and Bayesian Boosting, were applied in order to detect anemia. After the experiments' evaluation, the Stacking model with the combination of the Decision Tree (DT) and K-Nearest Neighbor as base classifiers and NB as meta classifier achieved a higher accuracy of 92.12%.

In [44], the authors based on CBC data obtained from pathology centres to examine supervised ML techniques and models for the detection of anemia. In comparison to LR, LASSO and Exponential smoothing, the results outlined that the NB model outperforms the other ones in terms of accuracy (92.08%).

Similarly, in [45], supervised ML models, namely, NB, Random Forest (RF) and DT were evaluated and compared to predict anemia based on CBC data. The results showed that the NB model prevailed achieving an accuracy of 96.09%.

A Multi-label Classification technique is applied in the work [46]. The authors attempt to categorize patients with anemia according to its type with the contribution of the machine learning models. The Multilayer Perceptron (MLP) and SVM are nearly always the best classifiers, with MLP being significantly better according to the AUC.

Finally, in [47], multi-class classification algorithms for the diagnosis of anemia were applied. The authors used feature selection with majority voting to identify the key attributes in the input patient data set. Also, the Synthetic Minority Oversampling Technique (SMOTE) was performed on the imbalanced dataset. The experimental results indicated that the MLP model showed the best results.

III. Dataset Description and Analysis

This section describes the collection method and the features of the publicly available data [48], which was used for the validation of the learning models' performance in the adopted methodology for predicting anemia level.

The CBC test was applied to generate the data set parameters. A Hematology analyzer performed this test following standard operating protocols to determine the prevalence of different types of Anemia treated at the Eureka diagnostic center in Lucknow, India. The diagnostic center performed 4 – 8 CBC investigations a day on average. A collection of data was gathered between September and December 2020, and 1000 CBC investigations were performed. Exclusion criteria: i) adult males and females who are pregnant and older than 15 years old in the study population, ii) infants, young children less than 10 years old and pregnant women. After excluding the above categories of persons from the randomly selected sample of 400 subjects, the final data set consisted of 364 records and 11 features that were used to represent the involved subjects. In Table I, we list these features and provide a statistical description of them.

For characterizing anemia levels (which will be the target classes labels), we based on the haemoglobin (HGB) values [47] and formulated the next rules based on World Health Organization (WHO) criteria [49]:

- Female: HGB$\geq$12 normal, 11$\leq$ HGB $<$ 12 mild, 8 $\leq$ HGB $<$ 11 moderate, HGB$<$8 severe
- Male: HGB$\geq$13 normal, 11$\leq$ HGB $<$ 13 mild, 8 $\leq$ HGB $<$ 11 moderate, HGB$<$8 severe

In addition, in the specific data, anemia prevalence and association with age and gender is depicted in Figure 1. Focusing on the risk factor of age, all anemia levels are observed in all age groups with the severe level consisting of very few instances. As for gender, a small sample of men and women are equally distributed in the severe class. Also, men dominate in the normal and mild classes, while women

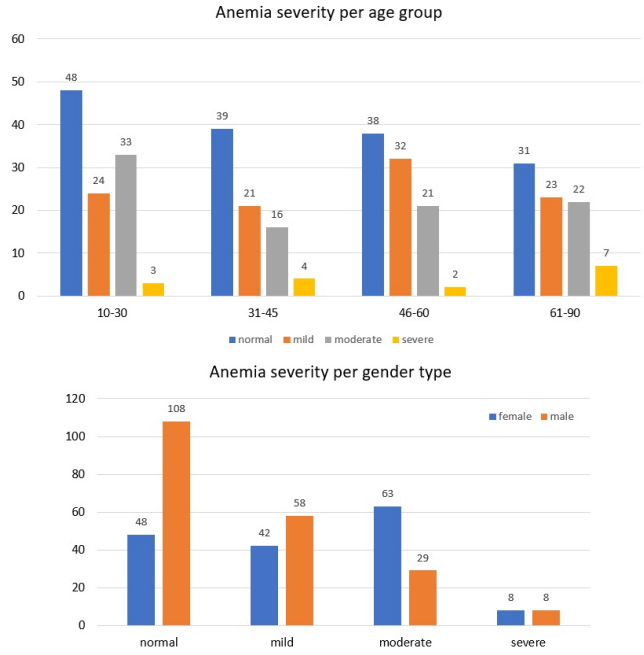

Fig. 1. Anemia prevalence in terms of age and gender type.

stand out (with at least double presence) in the moderate class. The distribution of subjects into four classes is 156 - 42.86% (normal), 100 - 27.47% (mild), 92 - 25.27% (moderate) and 16 - 4.39% (severe). Although the dataset is imbalanced (mainly towards the "sever" class), no technique has been applied to make the class distribution uniform.

IV. Methodology

The problem of predicting the anemia level will be treated as a multi-class classification and, therefore will be solved by adopting two different strategies: OVA and OVO.

Assuming that M stands for the number of severity levels, in our case M will be equal to 4 (including the normal level). The first strategy (OVA) uses the instances belonging to one of the M classes and solves M binary sub-tasks where, each time, class "yes" consists of the samples of one severity level, while class "no" is formulated by the samples stemming from the rest of classes. On the contrary, the second strategy breaks down and solves $\frac{M(M-1)}{2}$ binary classification sub-tasks. The final decision is based on the outcomes of multiple classifiers. Figure 2 illustrates how the specific strategies are adapted to anemia level prediction.

The binary classification problems will be solved using the learning models LR and SVM. Therefore, in the next paragraphs, we will explain how the specific models achieve the anemia level classification of a subject.

a) Logistic Regression: LR [50] uses a logistic function to model a binary output variable ranging between 0 and 1. Also, logistic regression applies a nonlinear log transformation to the odds ratio, where odds = $\frac{p}{1-p}$ (p is the probability of an event occurring divided by the probability $1-p$ of an event not occurring) and then the logit function $logit(p)$ can take any real number in $(-\infty, +\infty)$:

$$logit(p) = \begin{cases} 0 & \text{if } p = 0.5 \\ < 0 & \text{if } p > 0.5 \\ > 0 & \text{if } p < 0.5 \end{cases}. \quad (1)$$

If the probability is greater than 0.5, the predictions will be classified as class "no". Otherwise, class "yes" will be assigned.

b) Support Vector Machine: SVM [51] aims to find the best classification function to discern the instances of the two classes in the training data. Once this function is found, a new instance u can be classified by examining the sign of the function $f(u)$; if $f(u) > 0$, the u belongs to the positive class. SVM is a popular kernel-based classification algorithm in pattern recognition. Assuming that u and v are the feature vectors of two instances in the dataset, the most common kernel functions are defined as follows.

- A linear kernel is the simplest function represented by $k(u, v) = u^T v + c$, where the first term is the inner product of features vector u, v and c is an optional constant.
- A polynomial kernel is non-stationary and compatible with problems where all the training data is normalized. It is calculated by

$$k(u, v) = (\gamma u^T v + c)^d, \quad (2)$$

  where γ, c and d are adjustable parameters that stand for the slope, constant term and polynomial degree, respectively.
- A radial basis kernel function is denoted as

$$k(u, v) = \exp\left\{-\gamma \| u - v \|^2\right\}, \quad (3)$$

  where $\gamma = \frac{1}{2\sigma^2}$ and σ is an adjustable parameter for measuring the performance of the kernel. It measures the similarity between pairs of data points based on their distance in the feature space.
- A sigmoid kernel function is represented by

$$k(u, v) = tanh(\gamma u^T v + c), \quad (4)$$

  where γ and c are the adjustable parameters. A common value for γ is $\frac{1}{N}$, where N is the number of features in the dataset.

Notation:u^T denotes the transposition of vector u, $\|u\|$ denotes the Euclidean norm of vector u, $u^T v$ term is the inner product of vectors u, v and tanh$(\cdot)$ is the hyperbolic tangent function.

V. Results and Discussion

In this section, we will show the outcomes of the experiments executed following the strategies OVO and OVA. The performance of these approaches is evaluated assuming the LR and SVM models. In both strategies and considered models, 10-fold cross-validation was applied. In this method, the dataset is separated into 10 different subsets where each

TABLE I
LIST OF FEATURES AND STATISTICAL DESCRIPTION IN THE DATASET.

Feature	Type	Notation	Description	Limitis	Min-Max	Mean± std
Age	Numerical	age	Current age of the patients	11 - 100 (years)	11 - 89 (years)	44.92 ± 18.78
Gender	character	gender	Gender	Male (203) /Female (161)	-	-
Hemoglobin	Numerical	HGB	Level of HGB	11-16 g/dL	4.2-19.6	11.91 ± 2.19
Mean cell volume	numerical	MCV	Level of MCV	80-101 fL	55.7-124.1	87.51 ± 9.33
Mean cell hemoglobin	numerical	MCH	Level of MCH	27-32 pg	14.7-41.4	28.23±3.87
Mean cell hemoglobin concentration	numerical	MCHC	Level of MCHC	31-37 g/dL	23.6-50.2	32.05± 2.80
Red cell distribution width	numerical	RDW	Level of RDW	11 -16	10.6 -29.2	15.12±2.18
Red blood cell count	numerical	RBC	Level of RBC	3.80-4.80 M/uL	1.36-6.90	4.28.6 ±0.82
White blood cell count	numerical	WBC	Level of WBC	3.5-11.5 ths/uL	2 - 42.42	8.86 ± 4.87
Platelet count	numerical	PLT	Level of PLT	150-450 (10^3/uL)	10-660	223.75±99.41
Packed cell volume	numerical	PCV	Level of PCV	36-46	13.1-56.9	36.76±6.83

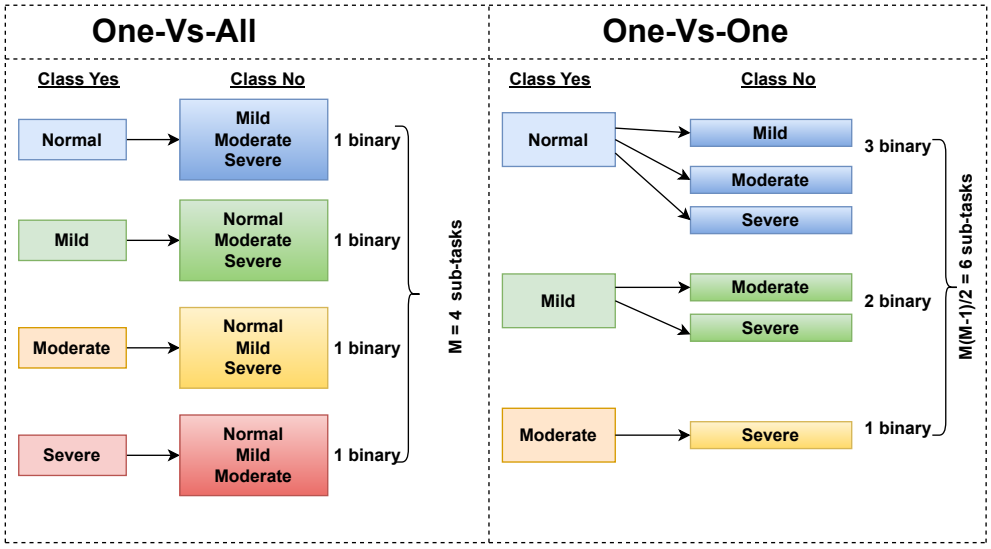

Fig. 2. Multi-class Classification strategies for anemia level prediction.

time one subset constitutes the test set, and the remaining 9 ones are used as training sets in turn. In this way, all the combinations are tested and the performance score is obtained by taking the average of each result.

A. Experiments environment

WEKA software tool [52] was utilized for the execution of the experiments by exploiting the libraries LibSVM and MultiClassClassifier. The former helped us to experiment with different types of kernel functions for the identification of the one that achieves the best performance. The latter provided us with an interface through which we tested the two strategies mentioned above, OVO and OVA. It should be noted that in the OVO case the field "PairWiseCoupling" was set to true.

The system on which the experimental measurements were performed had the following characteristics: 11th generation Intel(R) Core(TM) i7-1165G7 @ 3.2 GHz, 32 GB RAM, Windows 11 Pro, 64-bitOS and x64 processor.

B. Evaluation metrics

The performance evaluation of the investigated models and strategies was based on the accuracy, precision, recall and AUC, demonstrated in Table II under 10-fold cross-validation. These metrics for the multi-class case are captured as the weighted average of the class-wise score of each metric, namely multiplied by the weight of the class or frequency of the class on the entire dataset divided by the sum of the weights. So, the weighted average metrics [53] are as follows:

$$Precision = \frac{\sum_{i=1}^{K} w_i \frac{TP_i}{TP_i+FP_i}}{\sum_{i=1}^{K} w_i} \quad (5)$$

$$Recall = \frac{\sum_{i=1}^{K} w_i \frac{TP_i}{TP_i+FN_i}}{\sum_{i=1}^{K} w_i} \quad (6)$$

$$AUC = \frac{\sum_{i=1}^{K} w_i AUC_i}{\sum_{i=1}^{K} w_i} \quad (7)$$

$$Accuracy = \frac{\sum_{i=1}^{K} w_i \frac{TN_i+TP_i}{TN_i+TP_i+FN_i+FP_i}}{\sum_{i=1}^{K} w_i}, \quad (8)$$

where TP, TN, FP, FN capture the class-wise true positive/negative and false positive/negative and $w_1 = 156, w_2 = 100, w_3 = 92, w_4 = 16$ stand for the number of instances per class label in the dataset.

TABLE II
MULTI-CLASS CLASSIFICATION STRATEGIES EVALUATION IN TERMS OF PRECISION, RECALL AND AUC.

Class	OVA - LR			OVO - LR			OVA - Polynomial SVM d = 2, c=1, $\gamma = 0.1$			OVO - Linear SVM		
	Precision	**Recall**	**AUC**	**Precision**	**Recall**	**AUC**	**Precision**	**Recall**	**AUC**	**Precision**	**Recall**	**AUC**
normal	0.974	0.974	0.992	0.962	0.968	0.994	0.762	0.942	0.958	0.943	0.955	0.969
mild	0.788	0.630	0.916	0.939	0.920	0.979	0.589	0.560	0.805	0.896	0.860	0.928
moderate	0.682	0.815	0.934	0.957	0.957	0.994	0.706	0.522	0.877	0.925	0.935	0.982
severe	0.833	0.938	0.992	0.882	0.938	0.992	0.625	0.313	0.785	0.882	0.938	0.995
Weighted Average	0.843	0.838	0.956	0.951	0.951	0.990	0.694	0.703	0.888	0.923	0.923	0.962

C. Results

Table II summarizes the performance of LR and SVM under the two multi-class classification strategies.

Also, as for the SVM model, we investigated which parameters and kernel functions (as the one presented in Section IV) would give us the highest scores. We concluded that the linear SVM was the most efficient presenting high classification performance under the OVO strategy. However, in the case of the OVA strategy, only the polynomial kernel function of $d = 2$ (see Eq.2) gave us an acceptable performance against other parameter settings. However, for other datasets or problems, the optimal value may be different.

Next, we show, in ascending order, the accuracy of the models per strategy. More specifically, the outcomes are the following:

- Accuracy = 70.33% - OVA polynomial SVM ($d = 2, \gamma = 0.1, c = 1$)
- Accuracy = 83.79% - OVA LR
- Accuracy = 92.31% - OVO linear SVM
- Accuracy = 95.05% - OVO LR

As for the accuracy of the LR model, under the OVA strategy, it was 13.46% higher than the SVM's model in the same strategy and 11.26% lower than the LR's model in the OVO strategy.

Focusing on the rest metrics, as for the OVO strategy, the LR noted essentially superior classification scores with average precision and recall equal to 0.951 and an AUC of 0.990. In terms of the OVA strategy, again, LR was the dominant model which indicated average precision and recall equal to 0.843 and 0.838, respectively, and an AUC of 0.956. Comparing the average results of the best-performing model in each strategy, the experiments unveiled the LR as the most appropriate. Moreover, the specific model exhibited constantly high class-wise performance and the highest accuracy of 95.05%.

Also, all models presented high AUC indicating an increased discrimination ability between the classes that capture anemia levels. Regarding the models' sensitivity, the OVA strategy, especially with polynomial SVM, indicated low levels to all class labels except for the normal one, while the severe class presented the worst performance (0.313). It is essential to mention that currently, no resampling technique (e.g., SMOTE) has been applied before the models' training to tackle the issue of class imbalance. However, this issue was efficiently handled by both strategies with the LR model and OVO with linear SVM. To sum up, OVO with the LR model is the main suggestion of the current analysis for anemia level prediction.

VI. CONCLUSIONS

In conclusion, this study presented a multi-class classification framework for predicting the anemia level. Through experiments and performance evaluation, the OVO strategy resulted as the most efficient both class-wise and on average succeeding accuracy of 95.05%, precision and recall of 0.951 and AUC of 0.951, using the LR to solve the binary classification subtasks. In future work, we aim to deal with feature ranking and selection techniques in order to reduce the models' complexity by selecting the most important features for the anemia level prediction and investigating, to what extent, the models' performance is enhanced or not. Finally, alternative multi-class classification models and/or schemes in combination with class balancing techniques will be assessed and compared to the strategies evaluated here.

ACKNOWLEDGMENT

This research was funded by the European Union and Greece (Partnership Agreement for the Development Framework 2014-2020) under the Regional Operational Programme Ionian Islands 2014-2020, project title: "Indirect costs for project "TRaditional corfU Music PresErvation through digiTal innovation" ", project number: 5030952.

REFERENCES

[1] J. Turner, M. Parsi, and M. Badireddy, "Anemia," in *StatPearls [Internet]*. StatPearls Publishing, 2022.
[2] T. G. DeLoughery, "Iron deficiency anemia," *Medical Clinics*, vol. 101, no. 2, pp. 319–332, 2017.
[3] M. J. Gamit, H. S. Talwelkar *et al.*, "Survey of different types of anemia." *International Journal of Medical Science and Public Health*, vol. 6, no. 3, pp. 493–496, 2017.
[4] P. Bhadra and A. Deb, "A review on nutritional anemia," *Indian Journal of Natural Sciences*, vol. 10, no. 59, pp. 18 466–18 474, 2020.
[5] G. M. Brittenham, G. Moir-Meyer, K. M. Abuga, A. D. Mitra, C. Cerami, R. Green, S.-R. Pasricha, and S. H. Atkinson, "Biology of anemia: a public health perspective," *The Journal of Nutrition*, 2023.
[6] G. Weiss, T. Ganz, and L. T. Goodnough, "Anemia of inflammation," *Blood, The Journal of the American Society of Hematology*, vol. 133, no. 1, pp. 40–50, 2019.
[7] H. Ludwig and K. Strasser, "Symptomatology of anemia," in *Seminars in oncology*, vol. 28. Elsevier, 2001, pp. 7–14.
[8] K. F. Lasch, C. J. Evans, and D. Schatell, "A qualitative analysis of patient-reported symptoms of anemia," *Nephrology Nursing Journal*, vol. 36, no. 6, p. 621, 2009.

[9] S. Kundrapu and J. Noguez, "Laboratory assessment of anemia," *Advances in clinical chemistry*, vol. 83, pp. 197–225, 2018.

[10] J. Válka and J. Čermák, "Differential diagnosis of anemia." *Vnitrni lekarstvi*, vol. 64, no. 5, pp. 468–475, 2018.

[11] L. T. Goodnough and A. K. Panigrahi, "Blood transfusion therapy," *Medical Clinics*, vol. 101, no. 2, pp. 431–447, 2017.

[12] I. Anand and P. Gupta, "How i treat anemia in heart failure," *Blood, The Journal of the American Society of Hematology*, vol. 136, no. 7, pp. 790–800, 2020.

[13] S. D. Pawar, S. D. Deore, N. P. Bairagi, V. B. Deshmukh, T. N. Lokhande, and K. R. Surana, "Vitamins as nutraceuticals for anemia," *Vitamins as Nutraceuticals: Recent Advances and Applications*, pp. 253–279, 2023.

[14] A. S. A. Sharourou, M. A. Hassan, M. B. Teclebrhan, H. M. Alsharif, S. A. Alhamad, T. S. Alsinani *et al.*, "Anemia: Its prevalence, causes, and management," *The Egyptian Journal of Hospital Medicine*, vol. 70, no. 10, pp. 1877–1879, 2018.

[15] L. Khan, "Anemia in childhood," *Pediatric annals*, vol. 47, no. 2, pp. e42–e47, 2018.

[16] E. Dritsas, M. Trigka, and P. Mylonas, "Ensemble machine learning models for breast cancer identification," in *IFIP International Conference on Artificial Intelligence Applications and Innovations*. Springer, 2023, pp. 303–311.

[17] E. Dritsas and M. Trigka, "Machine learning techniques for chronic kidney disease risk prediction," *Big Data and Cognitive Computing*, vol. 6, no. 3, p. 98, 2022.

[18] N. Fazakis, O. Kocsis, E. Dritsas, S. Alexiou, N. Fakotakis, and K. Moustakas, "Machine learning tools for long-term type 2 diabetes risk prediction," *IEEE Access*, vol. 9, pp. 103 737–103 757, 2021.

[19] E. Dritsas and M. Trigka, "Data-driven machine-learning methods for diabetes risk prediction," *Sensors*, vol. 22, no. 14, p. 5304, 2022.

[20] E. Dritsas, S. Alexiou, I. Konstantoulas, and K. Moustakas, "Short-term glucose prediction based on oral glucose tolerance test values." in *HEALTHINF*, 2022, pp. 249–255.

[21] S. Alexiou, E. Dritsas, O. Kocsis, K. Moustakas, and N. Fakotakis, "An approach for personalized continuous glucose prediction with regression trees," in *2021 6th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM)*. IEEE, 2021, pp. 1–6.

[22] E. Dritsas and M. Trigka, "Efficient data-driven machine learning models for cardiovascular diseases risk prediction," *Sensors*, vol. 23, no. 3, p. 1161, 2023.

[23] E. Dritsas, S. Alexiou, and K. Moustakas, "Cardiovascular disease risk prediction with supervised machine learning techniques." in *ICT4AWE*, 2022, pp. 315–321.

[24] M. Trigka and E. Dritsas, "Long-term coronary artery disease risk prediction with machine learning models," *Sensors*, vol. 23, no. 3, p. 1193, 2023.

[25] E. Dritsas, S. Alexiou, and K. Moustakas, "Efficient data-driven machine learning models for hypertension risk prediction," in *2022 International Conference on INnovations in Intelligent SysTems and Applications (INISTA)*. IEEE, 2022, pp. 1–6.

[26] E. Dritsas, N. Fazakis, O. Kocsis, N. Fakotakis, and K. Moustakas, "Long-term hypertension risk prediction with ml techniques in elsa database," in *Learning and Intelligent Optimization: 15th International Conference, LION 15, Athens, Greece, June 20–25, 2021, Revised Selected Papers 15*. Springer, 2021, pp. 113–120.

[27] E. Dritsas and M. Trigka, "Supervised machine learning models to identify early-stage symptoms of sars-cov-2," *Sensors*, vol. 23, no. 1, p. 40, 2022.

[28] M. Trigka, E. Dritsas, and P. Mylonas, "Mental confusion prediction in e-learning contexts with eeg and machine learning," in *Novel & Intelligent Digital Systems Conferences*. Springer, 2023, pp. 195–200.

[29] E. Dritsas and M. Trigka, "Lung cancer risk prediction with machine learning models," *Big Data and Cognitive Computing*, vol. 6, no. 4, p. 139, 2022.

[30] I. Konstantoulas, E. Dritsas, and K. Moustakas, "Sleep quality evaluation in rich information data," in *2022 13th International Conference on Information, Intelligence, Systems & Applications (IISA)*. IEEE, 2022, pp. 1–4.

[31] I. Konstantoulas, O. Kocsis, E. Dritsas, N. Fakotakis, and K. Moustakas, "Sleep quality monitoring with human assisted corrections." in *IJCCI*, 2021, pp. 435–444.

[32] E. Dritsas and M. Trigka, "Supervised machine learning models for liver disease risk prediction," *Computers*, vol. 12, no. 1, p. 19, 2023.

[33] M. Trigka and E. Dritsas, "Predicting the occurrence of metabolic syndrome using machine learning models," *Computation*, vol. 11, no. 9, p. 170, 2023.

[34] E. Dritsas, S. Alexiou, and K. Moustakas, "Metabolic syndrome risk forecasting on elderly with ml techniques," in *International Conference on Learning and Intelligent Optimization*. Springer, 2022, pp. 460–466.

[35] E. Dritsas and M. Trigka, "Stroke risk prediction with machine learning techniques," *Sensors*, vol. 22, no. 13, p. 4670, 2022.

[36] N. Fazakis, E. Dritsas, O. Kocsis, N. Fakotakis, and K. Moustakas, "Long-term cholesterol risk prediction using machine learning techniques in elsa database." in *IJCCI*, 2021, pp. 445–450.

[37] E. Dritsas and M. Trigka, "Machine learning methods for hypercholesterolemia long-term risk prediction," *Sensors*, vol. 22, no. 14, p. 5365, 2022.

[38] E. Dritsas, M. Trigka, and P. Mylonas, "A multi-class classification approach for weather forecasting with machine learning techniques," in *2022 17th International Workshop on Semantic and Social Media Adaptation & Personalization (SMAP)*. IEEE, 2022, pp. 1–5.

[39] Y. Liu, J.-W. Bi, and Z.-P. Fan, "A method for multi-class sentiment classification based on an improved one-vs-one (ovo) strategy and the support vector machine (svm) algorithm," *Information Sciences*, vol. 394, pp. 38–52, 2017.

[40] E. Dritsas, S. Alexiou, and K. Moustakas, "Copd severity prediction in elderly with ml techniques," in *Proceedings of the 15th International Conference on PErvasive Technologies Related to Assistive Environments*, 2022, pp. 185–189.

[41] T. K. Yıldız, N. Yurtay, and B. Öneç, "Classifying anemia types using artificial learning methods," *Engineering Science and Technology, an International Journal*, vol. 24, no. 1, pp. 50–70, 2021.

[42] A. Dixit, R. Jha, R. Mishra, and S. Vhatkar, "Prediction of anemia disease using machine learning algorithms," in *Intelligent Computing and Networking: Proceedings of IC-ICN 2022*. Springer, 2023, pp. 229–238.

[43] P. T. Dalvi and N. Vernekar, "Anemia detection using ensemble learning techniques and statistical models," in *2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)*. IEEE, 2016, pp. 1747–1751.

[44] C. Sasikala, M. Ashwin, M. Dharanessh, and M. Dhanabalan, "Curability prediction model for anemia using machine learning," in *2022 8th International Conference on Smart Structures and Systems (ICSSS)*. IEEE, 2022, pp. 1–7.

[45] M. Jaiswal, A. Srivastava, and T. Siddiqui, "Machine learning algorithms for anemia disease prediction: Select proceedings of ic3e 2018," *ResearchGate. DOI*, vol. 10, pp. 978–981, 2019.

[46] C. Bellinger, A. Amid, N. Japkowicz, and H. Victor, "Multi-label classification of anemia patients," in *2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA)*. IEEE, 2015, pp. 825–830.

[47] R. Vohra, A. Hussain, A. K. Dudyala, J. Pahareeya, and W. Khan, "Multi-class classification algorithms for the diagnosis of anemia in an outpatient clinical setting," *Plos one*, vol. 17, no. 7, p. e0269685, 2022.

[48] "Anemia dataset," https://data.mendeley.com/datasets/dy9mfjchm7/1, (accessed on 30 September 2023).

[49] M. B. Mengesha and G. B. Dadi, "Prevalence of anemia among adults at hawassa university referral hospital, southern ethiopia," *BMC hematology*, vol. 19, pp. 1–7, 2019.

[50] E. Bisong and E. Bisong, "Logistic regression," *Building Machine Learning and Deep Learning Models on Google Cloud Platform: A Comprehensive Guide for Beginners*, pp. 243–250, 2019.

[51] S. Chidambaram and K. Srinivasagan, "Performance evaluation of support vector machine classification approaches in data mining," *Cluster Computing*, vol. 22, pp. 189–196, 2019.

[52] "Weka," https://www.weka.io/, (accessed on 30 September 2023).

[53] T. Kautz, B. M. Eskofier, and C. F. Pasluosta, "Generic performance measure for multiclass-classifiers," *Pattern Recognition*, vol. 68, pp. 111–125, 2017.