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VitaDNet: A Deep Learning-Based Approach for Vitamin-D Deficiency Prediction

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Abstract. Vitamin D (VD) deficiency is a very common disease among elderly people. The lack of VD causes various diseases related to skin, eyes and throat. The previous epidemiological studies tried to predict the vitamin B6 and VD levels from the blood samples. Since this is laborious and time-taking, it is very difficult for the homely people to work on it. There is a strong requirement for the noninvasive method as there is a necessity to detect the deficiency at the early stage. Certain crucial parameters that could be used for analysis are based on the intake of anthropogenic parameters along with the commonly known body vitals. These parameters include the body mass index (BMI), waist circumference (WC), waist-to-height ratio (WHR) and body roundness index (BRI). The dataset used for the prediction of VD has been collected from 501 patients in the age of 40–75 years old. The prediction of VD levels in the body has various complications, like the sex, previous health records, inherent health conditions and body pathology. To consolidate all those parameters and to analyse, a robust model is required to associate the parameters which are used to predict the deficit of VD. A binary set of gated recurrent units (GRUs) are used along with the auto-encoders. The feature extraction and selection module in the network are composed of two different patch-based networks which makes the three-stage network robust. Despite these difficulties, the model is robust enough to predict the levels of VD in the body based on the anthropogenic parameters. To support this network, a sub-VitaDNet module is proposed based on the food taken. Through this network, the food taken is continuously observed and the levels of VD are predicted. Hence, the authors believe that the model is robust enough to predict the VD levels in the body.

Keywords: Anthropometries; sub-networks; vitamin D; GRU; prediction; auto-encoders.

1. Introduction

Vitamin deficiency is one of the most common disorders the world is facing. The symptoms of the vitamin deficiency include psychiatric changes, decrease of the

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blood cells like neutrophils, white blood cells, red blood cells and haemoglobin in blood and the insulin levels of the body. In some patients, a decrease in the vitamin levels might lead to psychiatric diseases like schizophrenia, bipolar disorders and attention disorders. Many of the studies show that the inverse associations of the hydroxyvitamin-D levels to the body mass index (BMI) of the human body. The adiposity of the human body is closely related to the cardio-vascular diseases, diabetes mellitus, hypertension (Nkembe *et al.*, 2009; Mirti *et al.*, 2011; Ravani *et al.,* 2009) and the bronchial diseases of the human body. BMI of the human body is the widely used metric to validate the pathological positions of the human body. Waist circumference (WC) is the primary scoring metric to find the obesity levels in human beings. However, these metrics have various limitations and many advanced techniques, like lipid profile testing and visceral adiposity index (VAI), are proposed. The deficiency of the vitamins is one of the factors that causes various diseases. Since, the hydroxyamino components are highly required for the human body and only produced from the vitamin D (VD) after the protein–ligand interactions. The investigations on the necessity of VD to the human body along with the co-relations to the diseases has gained a lot more interest. Identification of vitamin deficiency helps in analysing the physiology of the human body. A great discovery of new patterns of the cause is needed at this point to ensure that the prevention of health measures could be implanted in an effective way. Traditional biochemical and invasive procedures used to determine VD levels are very expensive and it is a time consumption process. Additionally, the deficit in VD leads to various other diseases consequently. Hence, diagnosing the deficiency in VD is much required so that the treatment could be done rapidly. The research gap thus identified made us work on a model which should be robust and do the process rapidly. Moreover, it would be still better if the model predicts the association of VD with any other disease. There are many works in which the vitals of the human body have been analysed based on the physical and pathological features. Considering all these factors, the VITA model has been proposed which detects the VD based on anthropogenic metrics and in addition heart cancer could also be predicted based on the deficit. The noninvasive method describes "a procedure that does not require inserting an instrument through the skin or into a body opening". The primary objective of this work is to devise a robust model that could be a noninvasive method. The main intention of this work is to focus on collecting the breath signals along with the heartrate for analysis of deficit of VD. There are more consequences of diseases that might occur due to the deficit of VD. Second, the objective is to determine the association of heart cancer and VD. Correlation among these two could be assessed based on the factors such as the signals from the heart that could be retrieved through the PPG. As this model collects data from various sensors to analyse, there are opportunities for the noise to be included along with the data. Hence, the model requires more attention to remove the noise. Finally, there is a correlation between the VD and heart cancer. The paper structure is provided as given below. Related works have been discussed in the next section. Proposed VITANET model has been demonstrated and illustrated in the section followed by experiments and results. At the end, conclusion along with the summarization of the results has been provided.

2. Related Works

In order to predict the severity of VDD, statistical models like linear regression (LR), multivariable adaptive regression spline, support vector regression (SVR), and SVR classifiers (SVR-C) (Bechrouri *et al.*, 2009) have traditionally been employed with questionnaires (Guo *et al.*, 2013). Previous studies did not employ machine learning methods for the severity prediction and the inferences from various works were compared with statistical models. The severity of VDD is predicted using a typical statistical model, like LR, however it performs poorly due to its limited predictive performance and numerous factors. Prediction of VD value has been done based on the biochemical metrics such as gender and age. Merlijn *et al.* (2018), Sohl *et al.* (2014) and Naureen *et al.* (2020) a set of questionnaires has been considered for predicting the VD. The authors in Bechrouri *et al.* (2019) have done an assessment of models such as linear model, MARS, logistic regression and SVR. From their experimental results, the prediction done by SVR shows a promising accuracy when compared with the other models. Gonoodi *et al.* (2019) deployed the decision tree to evaluate the analysts that are related with the deficiency of VD. This model is used to influence the decision of the deficiency in VD through the blood count metrics together with the other variables. Additionally, this study also identified that the serum zinc is considered as a significant influence for the deficiency of VD and this work looks similar with Mohamadkhani *et al.* (2015). Apart from this, the association among the hepatitis B virus (HBV) and alpha-fetoprotein (AFP) has been examined and it has been concluded that the AFP creates a momentum in contributing towards the deficiency in VD through the deployment of decision trees and multivariate logistic models. The aim of the work in Carretero *et al.* (2021) is to find out the relationship of the various metrics such as BMI, WC, body roundness index (BRI), VAI and Clinica Universidad de Navarra-Body Adiposity Estimator (CUN-BAE) with the VD. The authors' next task was to investigate the anthropometric metrics that contribute much towards the prediction of VD levels. The experimental results obtained from LR, NB and RF were compared. It has been observed that the metrics such as WC, WHtR, VAI and BRI were used to assess the deficiency in male, whereas the metric CUN-BAE is used to predict in female. The LR model recorded the highest value in prediction. Area under the curve showed a promising value through the NB technique in WC, BMI, BRI and WHtR, while the LR model showed a prominent performance for CUN-BAE and VAI. The authors have done an extensive analysis by using the search terms "association of VD and cardio vascular disease (CVD), breast cancer (BC), PCOS and AIS".

2.1. *Effect of VD in CVD*

VD plays a significant role in the regulation of the minerals and bone. Additionally, it has its footprint in various diseases that includes CVD (Wang *et al.*, 2012). A deficit of serum levels of 25-hydroxyvitamin D [25(OH)D] leads to poor outcomes in CVD. Treatment to modify the serum levels are found to be reasonable. From various inferences, it has been evidenced that one billion people in the world might have a shortfall of 25(OH)D serum levels (Holick and Chen, 2018). According to the theory of VD impounding in adipose tissue, there is a meta-analysis which shows the reduction in obesity will have an impact on the VD supplementation in obese patients (de Oliveira *et al.*, 2020). Serum VD concentrations were found to be 38.17 nmol/L less in persons who suffer due to obese. An increase in VD doses did not lead to a significant increase in 25(OH)D plasma concentrations. Hence there is an imperious need to check for new strategies for optimal VD supplementation. Eventually, various studies showed that there is a strong relation of low plasma 25(OH)D with obesity in adults (Mai *et al.*, 2012), kids (Gilbert-Diamond *et al.*, 2010) and aging women (LeBlanc *et al.*, 2012). If there is a less intake of VD, it might result in obesity at later stages, metabolic syndrome (Gagnon *et al.*, 2012) and also the inception of obesity (Kamycheva *et al.*, 2003). Further, there are other studies that exhibit the relations among the VDR polymorphisms with adiposity markers and BMI. Apart from these studies (Ochs-Balcom *et al.*, 2011; Bienertová-Vašků *et al.*, 2017; Ye *et al.*, 2001; Xu *et al.*, 2005), there are a few inferences that show the correlation between polymorphisms of VDBP and CY27b1 (Jiang *et al.*, 2007) and BMI. There is a remarkable inference shown in Kazemian *et al.* (2019) about the polymorphisms in VDR might create an impact in the WC and primitive fat in people added with VD.

2.1.1. *VD and BC in women*

From Hossain *et al.* (2019), it is well known that the women diagnosed with BC are found to be deficient in VD, whereas potential cohort studies revealed that there is an adversative relationship among the serum levels of (25(OH)D3) and BC prognosis (Al-Azhri *et al.*, 2017; Goodwin *et al.*, 2009; Chlebowski, 2013). There are more possibilities of early death of BC patients due to the low VD levels (Huss *et al.*, 2019). It is observed that there is a chance of producing more than one effect of VD that might create an impact in the expression of a minimum of 200 genes (DeLuca *et al.*, 2013). de Sire *et al.* (2022) put efforts to determine the correlation between the deficiency in VD and osteoporosis in BC patients.

2.1.2. *Association of VD and PCOS*

VD acts as an essential need to maintain a healthy life and to obtain a feasible pregnancy. If the level of VD goes down, then it might result in complications in pregnancy and fertility (Barrett and McElduff, 2010; Rojansky *et al.*, 1992). As per the information collected by the National Health and Nutrition Examination Survey (NHANES) 2003–2006 data, deficiency of VD (i) = 20 ng/ml and an inadequate level of (21–30 ng/ml) are found to be high in women of reproductive age between 20 and 44 years by a probable occurrence of 11% and 26% correspondingly (Ginde *et al.*, 2009; Zhao *et al.*, 2012). Hence, as a result of this, it is understood that the deficiency in VD in reproductive age. Deficiency in VD is found to be more in women who are suffering from PCOS. There is a strong correlation between VD and symptoms of PCOS that includes hyperandrogenemia (Li *et al.*, 2011; Hahn *et al.*, 2006), BMI (Li *et al.*, 2011; Hahn *et al.*, 2006; Yildizhan *et al.*, 2009) and a high score in hirsutism.

2.1.3. *VD and acute ischemic stroke*

There is evidence (Park *et al.*, 2015; Yalbuzdag *et al.*, 2015; Daubail *et al.*, 2014) to prove that there is an association between a less quantity of VD resulting in poor consequences in patients who suffer from acute ischemic stroke (AIS). The authors have deployed LR and Extreme Gradient Boost (XGB) to analyse the association and they observed that the performance of XGB is better when compared with the LR. In Witham *et al.* (2010), a study has been conducted and analysed that the supplement quantity of VD increases the flow mediated dilatation in patients who suffer from stroke which is considered to be a famous prediction that contributes towards the CVD (Inaba *et al.*, 2010).

2.1.4. *VD and skin cancer*

A number of studies (Mahamat-Saleh *et al.*, 2020) have looked at the connection between dietary VD intakes (through food or supplements) or circulation levels of 25(OH)D and skin cancer risk (a biomarker of VD status reflecting both intake and synthesis related to sun exposure). Regarding 25(OH)D levels, the majority of research indicated a higher risk of melanoma and keratinocyte cancer (KC), whereas a few studies showed an opposite pattern or no correlation at all. High blood levels of 25(OH)D have been linked to an increased risk of KC, especially of BCC, despite a recent meta-analysis based on four studies finding no association between these levels and melanoma risk.

2.1.5. *VD and weight analysis in newborns*

Fetal growth is a complicated process that is influenced by a variety of intrauterine environmental elements, where the availability of nutrients and oxygen is crucial as well as the state of hormones, adipokines, oxidative stress (OS), and inflammation (Dede *et al.*, 2017). An increase in OS and inflammation have been observed in obese women (Westermeier *et al.*, 2014), which is likely to have an impact on fetal growth and raise the probability of giving birth to a baby who is small for gestational age (SGA). Increased risk of macrosomia or an LGA baby due to excessive maternal fat mass or prenatal weight increase (Westermeier *et al.*, 2014) has been linked to changes in the metabolic, inflammatory, and oxidative status. A retrospective cohort study, however, found that inadequate early weight gain was linked to a higher risk for SGA (Dede *et al.*, 2017; Westermeier *et al.*, 2014). Perichart-Perera *et al.* (2022) created an artificial neural network (ANN) model to predict whether there are any SGA newborn in pregnancies despite of obesity with various factors such as gestational weight gain (GWG), biochemical and OS indicators along with the first-trimester maternal body fat composition. A simulator which works based on the principle of ANN algorithm was created to anticipate the outcome of the SGA after an extensive analysis has been used to categorize maternal characteristics. This work aims to find the vitamin deficiency in the new-born babies. Many different parameters are considered in this study like excessive gestational weight, heart rate, and blood pressure levels. Many parameters combined can give a good prediction of different effects on the baby. There were many research works on the VD deficit and out of which a few works were based on the association of VD deficit with many other diseases. A small comparison among the evaluation of the models along with the association metrics is shown in Table 1, which provides a clear understanding of the parameters used for determining the relationship among the diseases. Allahyari *et al.* (2011) carried out this task further and proposed to predict the effect of VD and find the cardio metabolic levels. These levels are very crucial to make the heart moments smoother. These changes in the cardio-vascular mechanism leads to various heart diseases that can affect the patient for a longer time. Zhang *et al.* (2022) discussed a deep learning model in finding the VD levels and analysing the risk of the patients. XGBoost based training is performed in this model. The efficacy of the prediction made by the model is found to have discrepancies due to various factors, such as sample size and nature of the variables. In this analysis, anthropogenic parameters and human modalities are used to predict the VD levels in the human body. Based on the VD levels, CVD is predicted using the threshold levels of the VD levels. Previous research works have been focused either on invasive or noninvasive methods to predict the deficiency of VD levels. There were few limitations in those works, which are as follows:

- Study was done on a cohort group and on a particular region
- In few works, the dataset was found to be imbalanced
- Skin impedance parameters alone were considered for the prediction
- A few anthropometric metrics only were considered

Table 1. A detailed analysis about the relationship of VD with other diseases that researchers have worked on.

Ref.	Parameters	Association	Model	*	#	AUC/AIC	Limitations
de Sire *et al.* (2022)	Demographic and anamnestic data	Osteoporosis in BC patients	K-means clustering	—	—	AIC-976.45	Data taken for this analysis is small
Perichart-Perera *et al.* (2022)	Clinical, biomedical, nutritional and OS parameters (first trimester of pregnancy)	Excessive GWG, and OS predict SGA new-borns	ANN	—	—	0.8	The test was conducted in a health centre and hence prediction will not be applicable for all pregnant women. Self-reported p-BMI was used
Allahyari *et al.* (2011)	Anthropometric parameters	Cardio metabolic risk factors	ANN	66-low 66-medium 60-high	62-low 62-medium 63-high	70.3-low 66.9-medium 65-high	Adolescent girls' population were used in the study and it was carried during the month of January–March during which there might be an increase in VD.
Zhang *et al.* (2022)	Demographic, past history, personal and family history	Neurological deficit	LR (training and test set) XGBoost (training and test set)	— —	— —	0.727 0.761 0.818 0.786	Study was done on a small sample and the efficacy of the prediction made by the model is found to have discrepancies due to various factors such as sample size and nature of the variables
Kim *et al.* (2020)	Demographic and clinical characteristics	AIS	LR XGB	89.6 90.6	40.0 48.0	— —	—

* Indicates specificity; # indicates sensitivity

The objectives of this work are

- To make the noninvasive method effectual and determine the association of the VD and heart cancer
- Model optimization to be done since the parameters used for analysis might contain noise signals.

The novelty lies in considering the signals of breathe and as well as the heart rate through photoplethysmographic pulse signals apart from the other measures. A detailed analysis of these signals along with the VD levels is done to predict heart cancer.

3. VITA Model

In this study, a novel model is proposed to monitor the VD levels in human by continuously observing the body vitals through the sensors implanted to the patient's body. This health monitoring system aims to find the levels of VD effectively.

The work is completely an IoT-based system and it could also be accessed by the health expert remotely. The biosensors implanted on the body are used to find the anthropogenic dimensions of human, such as height, weight, breathe rate, heart rate, muscle specificity, stretchability and the electric activity of the central nervous system (CNS). This is shown in Fig. 1, where the five bodily implanted sensors continuously collect and transmit the data. The dataset used was recorded under the guidance of a concerned doctor in hospital. The whole system is divided into three major modules, which includes wearable devices, monitoring and transmission, health assessment and recommendations. These modules are discussed in the paper in detail.

3.1. *Sensor devices and monitoring*

The suggested IoT device is able to collect the data uninterruptedly and transmits to the health expert. The data collected from the sensors consists of blood pressure, pulse rate, heart rate, breathing rate, impulse activity of the nerves and muscle stretchability. In the modern era, different sensor devices are widely being used in the field of health to assess various diseases. The data is regularly transmitted to continuously monitor the health activity of the person. The physicians and the clinicians at the receiver location use this real time data to predict the VD levels in the human body. Signals could be generated from wearable devices like watches, wristbands and mobile phones could be used for the analysis. The chest band sensor that is deployed need not to be attached to skin whereas this can also be placed inside the pocket. The sensor set includes the ECG sensors, axis-accelerometer, proximity sensors, saturation sensors and the gyroscopes. The global sensor framework module is efficient enough and can be deployed into the existing

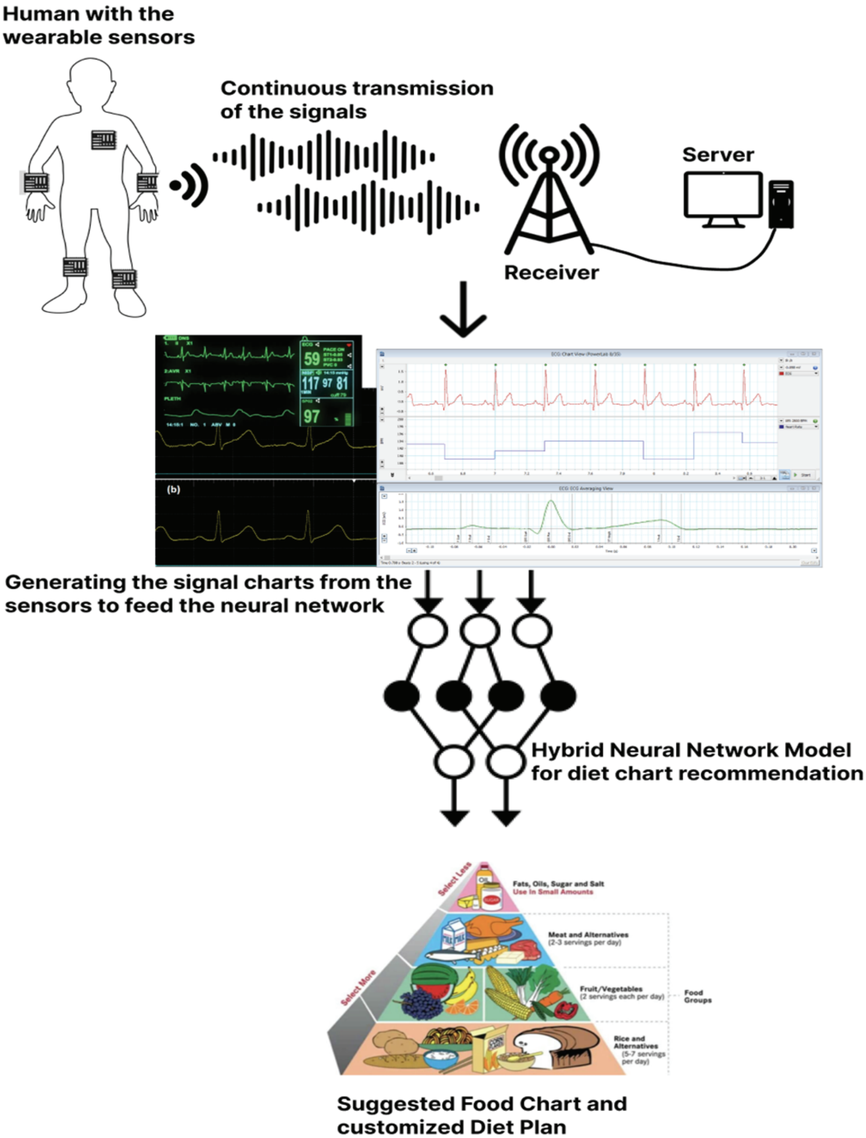

Fig. 1. VITA model skeleton.

devices effectively. The chest sensor setup and the wrist sensor used in this module can transmit and receive the signals from the global sensor module. This ensures the effective communication between all the sensors and measures the anthropogenic parameters effectively. A standard interference module is deployed in this framework, allowing the access to integrate all the local sensors to the global sensors. These sensors also support the multiple access to all the nearby local sensors on the basis of the *ad hoc* settings. This makes up a new body sensory network (BSN) module in the framework.

3.2. *Wireless communication of network*

The impact of the radiation while transmitting the data using signals is also to be considered. If not, it could raise other problems. In the proposed approach, low range communication is established between the local sensors and between the local sensors and global sensors. The design of the efficient IoT based health monitoring system is inevitable. Using the low-range frequency waves adds an advantage of the more battery time. In this paper, an optimized wireless transmission network is designed based on the sensory operating system. This mini-OS platform in the network ensures the data fragmentation and retransmission to run smoothly. All the local and global sensors transmit the data seamlessly all the time and relay on the single channel network. Moreover, the transmission protocol used in this study reduces the power consumption significantly.

3.3. *Deep neural network architecture*

The design of the neural network is presented in this section. The architecture of the VITA model is presented in Fig. 2. This diagram explains the workflow of the deep learning module briefly.

The topology of the proposed model contains input layer, output layer and many hidden layers activated with the combination of functions namely exponential linear unit (ELU) and sigmoid. The hidden layers present in this network are alternatively placed with ELU and sigmoid activation functions to ensure the smoothened results from the data. This also helps the learning to be involved between the layers

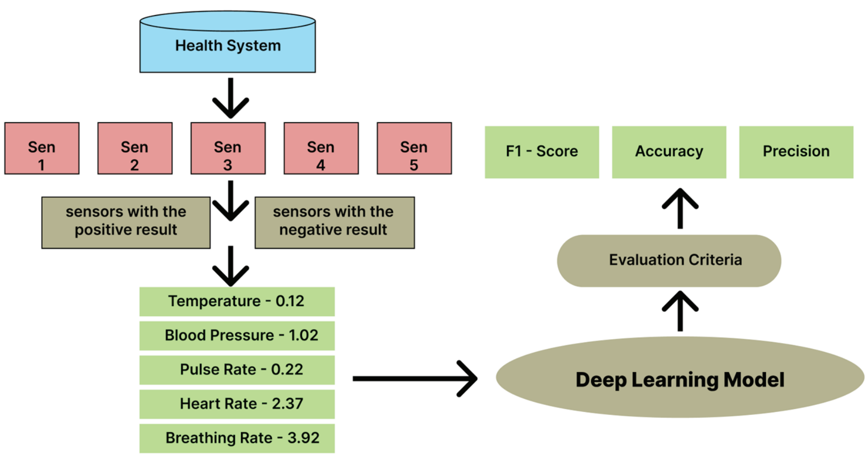

Fig. 2. Architecture of the VITA model.

Fig. 3. Sensors attached to the patient's body.

in an effective manner. The operative model of the neural network is depicted in Fig. 3. The mathematical expression of the model is given in Eq. (1)

$$Result_p = rl/\mathrm{sig}\left(\sum_{n=1}^{n} x_p weight_n^p + Bias_p\right). \tag{1}$$

The $Result_p$ in the given expression represents the resultant of a hidden layer p and the $weight_n^p$ in the equation is the weight of the layer p for a neuron n. The input features of the system is represented by the x_p. The activation function ELU is given as $rl(*)$. Two different activations, ELU and sigmoid, are used in the network, interchangeably, given in Eqs. (2) and (3)

$$\begin{aligned} \mathrm{ELU} &= \propto e^x \quad \text{if } x, \\ y &= x \quad \text{if } x > 0, \\ &\propto e^x - 1 \quad \text{if } x \le 0, \end{aligned} \tag{2}$$

$$\mathrm{Sigmoid} = \frac{1}{1 + e^{-x}}. \tag{3}$$

3.4. *Noise removal techniques*

There might be chances for the noise to be present in the data during the process of data collection. Among the various techniques, it has been determined that the principal component analysis (PCA) is the prominent technique that can be used for the dimensionality reduction in the data. This technique also ensures that the data is denoised. Using this technique, the data can be mapped to the original space presented in the new space. Parallelly, a new method to find the orthogonal transformation of this space is essential to generate a new space. The variance of the global data is also used to find the original space. The data dimensionality reduction is achieved in this network using a feature mapping mechanism. The reduced dimension of the data is smoothened by the N-dimensional features to the K-dimensional features. The dimensions that are discarded in the updated space are as the noise space. The algorithm of the VITA model is provided in the following steps.

Assumptions:
Sample data considered in this study X = x^a, x^b, x^c, x^d, …, x^i, …, x^z, that has a dimension feature as

$$X = x_i^1, x_i^2, x_i^3, x_i^4, \ldots, x_i^n .$$

Step 1: Mean is calculated each time for the ith feature to achieve the other sample given in Eq. (4)

$$X = \{x_i^{-1} - \overline{x_1}, x_i^{-2} - \overline{x_2}, x_i^{-3} - \overline{x_3}, \ldots, x_i^{-n} - \overline{x_n}\}. \tag{4}$$

Step 2: Covariance matrix of the x_i^n is calculated using the convolution matrix CM. From these operations the final covariance of the matrix computed using Eq. (5)

$$\mathrm{cov}(X1, X2) = \frac{\sum_p^k (x_i^2 - \overline{x_i})(x_i^2 - \overline{x_i})}{N - 1}. \tag{5}$$

Step 3: In this step, k number of values are selected as eigen values and proceeded.

The loss functions are used to make our model predictions more accurate. The usage of the loss function in the model should be optimized so as to enhance the accuracy and to make the model to function properly. This is carried out in the following section.

3.5. *Optimisation of the proposed model*

The loss function of the proposed model is optimised by the gradient descent algorithm as given in Eq. (6)

$$\alpha = \alpha - \eta\Delta \times func(\theta). \tag{6}$$

In Eq. (6), the model parameter and learning rate are represented by α and η. The $func(\theta)$ and $\Delta func(\theta)$ depict the loss function and the gradient loss function respectively. At each iteration, on the pair of the samples, these functions are updated which changes the accuracy of the model eventually. The equation of this stochastic process of gradient descent algorithm is given in Eq. (7)

$$\alpha = \alpha - \eta\Delta \times func(\theta;\ input;\ output). \tag{7}$$

The learning rate in this analogy is set manually and then optimised after the iterations. If this rate is too large, then it makes repetitive oscillations, if it is too low then it takes longer time to reach. AdaGrad is a similar optimization technique based on the gradient mechanism. In contrast to the classical gradient descent, this approach uses the concept of dynamic learning making the optimization very effective and superficial. The learning rate is dynamically computed based on the squared sum of the priori gradient. The learning rate update in such an approach is given in Eqs. (8) and (9)

$$Grad_{m,n} = Grad_{m,n-1} + \eta\Delta * func(\theta_{m,n})^2, \tag{8}$$

$$\theta_{m,n} = \theta_{m,n-1} - \frac{\eta}{\sqrt{\theta_{m,n}} + \delta}\Delta func(\theta). \tag{9}$$

The $Grad_{m,n}$ is the summation of squared gradient at the mth iteration hyperparameter in the prior n iterations. The $func(\theta)$ is the gradient calculated at the mth parameter in the nth iteration and the δ is a constant that prevents the denominator to be null. However, this computation $\frac{\eta}{\sqrt{\theta_{m,n}}+\delta}$ eventually leads to decrease in the learning rate by increasing the denominator part. This makes the learning rate approach zero. In the updated version, AdaDelta is proposed that adds an external coefficient ϖ to influence the long-time interval of the gradient in the training set. AdaDelta is updated by using $\theta_{m,n}$ formula as shown in Eqs. (10) and (11)

$$\begin{aligned} Grad_{m,n} &= \varpi\ Grad_{m,n} + (1-\varpi)\ \Delta \times func(\theta_{m,n})^2, \\ K(t) &= \psi_1 K(t-1) + (1-\psi_1)\ \Delta\ func(\theta), \\ Grad_{t-1} &= \psi_2\ Grad_{t-1} + (1-\psi_2)\ \Delta \times func(\theta_{m,n})^2, \end{aligned} \tag{10}$$

$$\begin{aligned} \widehat{K(t)} &= \frac{K(t)}{1-\psi_1}, \\ \theta_{m,n} &= \theta_{m,n-1} - \frac{\eta}{\sqrt{Grad_t} + \delta}\widehat{K(t)}, \end{aligned} \tag{11}$$

where $K(t)$ is the hyperparameter momentum of the tth iteration.

4. Experiments and Results

This study takes data from crowd sampling and from the sensor devices. These sensors capture important signals and transmit them to the ground stations. These signals capture the anthropogenic parameters of the human body like heart rate, breathing rate, pulse rate, height, weight, electric activity of the brain, pulse rate, muscle moments and bone fragility. These signals can be monitored and cleaned simultaneously that makes the model robust and efficient.

4.1. *Data measurement*

The blood oxygen levels measured by the sensor depend on various external factors. The absorption degree of the two lights of the sensors that measure the levels also play a crucial role in accurate measurement. The ratio of the infrared light to the red light is calculated based on the hardware surface. The sensor implanted at the hands is also capable of calculating the blood oxygen saturation of the body. SpO_2 are calculated with a data token of 15 bytes per seconds ECG signal and PPG signal. The sensor device is presented in Fig. 3.

4.2. *Data transmission*

The wearable sensors attached to the human body relays on the network node and finds the nearest source path. This data is measured and communicated through the nearest path information module. The wireless network module works in the stipulated area and relies on the measurement of the base data. This wireless transmission module contains a microcontroller, RF chipset, RF transceiver chip and a battery. This module is capable of transmitting ECG signals, PPG signals, blood oxygen levels and the pulse rate to the ground station where the processor carries the whole health monitoring module. The component structure optimisation used in this module adopts the miniOS programming functionalities. These components are modified in the position based on the signal strengths.

4.3. *Test results*

The primary performance of the tests shows that the chest band, wristband and ankle bands are effectively monitoring the anthropogenic conditions of the patients. All the readings computed by the sensors are effectively transmitted to the real-time health monitoring system using low-frequency relay network nodes. The shortest path is identified when the module is compared to the single network topology or the channelled network. The health monitoring system at the base system uses this information to perform the advanced analytics and compute the VD deficiency along with diet chart recommendation. However, the delay in the data transmission makes the model work slower. This is one of the limitations we observed. For this purpose, a large volume of the data is collected and stored in the server and the computation process is carried out without interruption. These results are compared with the existing monitoring system, showing the proposed model is robust and effective. The captured signals at the base station are depicted in Fig. 4.

The deep neural network module is evaluated using the area under the receiver operating characteristic (ROC) curve (AUC) terms. It is generally used to evaluate the model's binary classification accuracy in the interval of 0 and 1. The ROC curve contains the comparison of the false positive rate and true positive rate on both the X-axis and Y-axis. The left edge portion in the upper region is considered as the ideal point of the curve and steepness is measured in that direction. At this point of the curve, the true positive rate (TPR) value is maximum and false positive rate (FPR) value is minimum. The ROC curve of two different classes healthy and deficient. The ROC curve of the average classification is given as 98% and accurately predicts the VD deficiency, as shown in Fig. 5. The calculation of this VD deficiency also makes up to detect various disorders in the human body

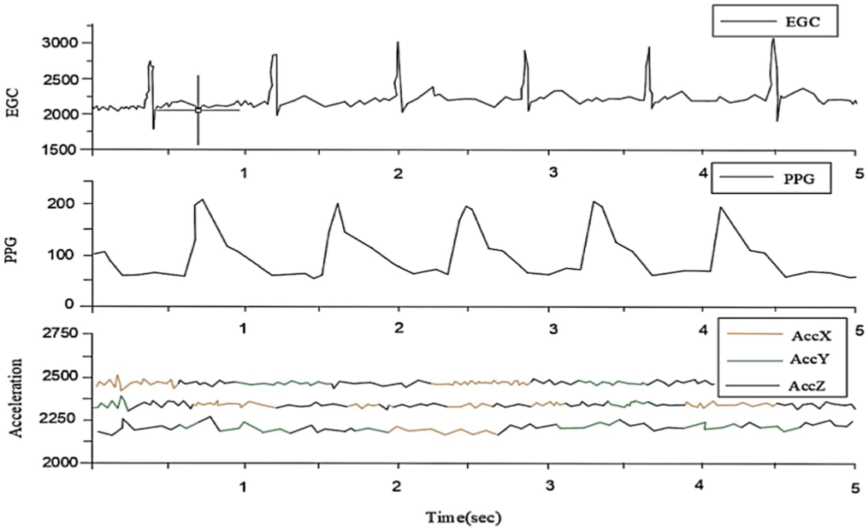

Fig. 4. Experimental performance of the data estimating the missing portions of ECG and PPG waveform.

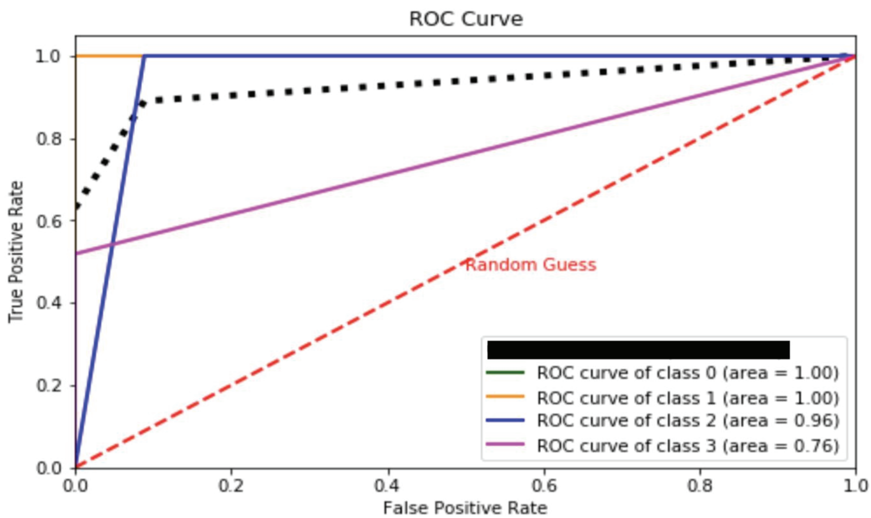

Fig. 5. The ROC curve of the proposed model gives the accuracy of 98%.

such as hypotension, hypertension, diabetics, sachmin schwazema, fragile bone disorder, etc.

The accuracy of the proposed model is compared with the other existing models. The results of comparison are presented in Fig. 6. The VitaDNet module is evaluated for the task of identifying the CVDs in the heart cancer screening task.

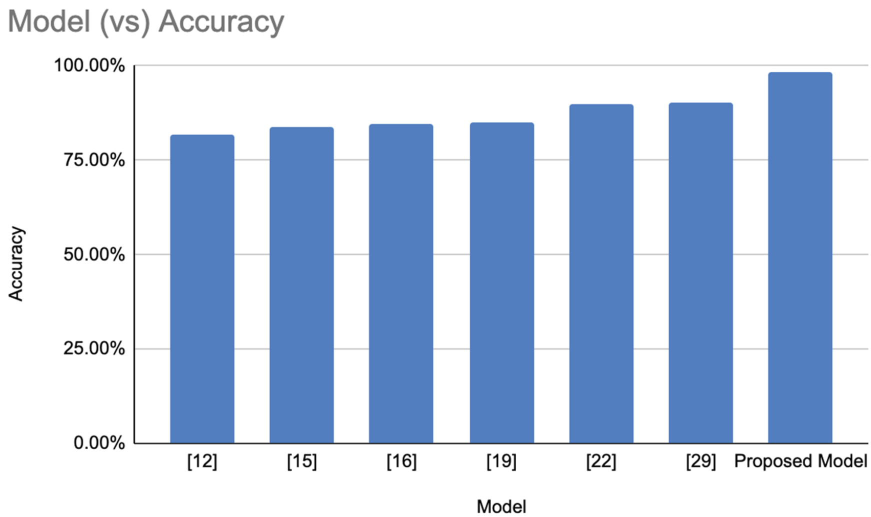

Fig. 6. The accuracy comparison of the proposed VITA model.

CVD Screening

	AUC	95% Confidence Interval	p Value
Our Model	0.871	0.860 - 0.882	-
DeepCAC	0.753	0.735 - 0.771	3e-29
KAMP-Net	0.725	0.700 - 0.749	1e-35
AE+SVM	0.684	0.659 - 0.711	1e-51

CVD Mortality Prediction

	AUC	95% Confidence Interval	p Value
Our Model	0.768	0.734 - 0.801	-
DeepCAC	0.696	0.655 – 0.737	0.0017
KAMP-Net	0.671	0.628 - 0.714	1e-5
AE+SVM	0.650	0.605 - 0.695	9e-8

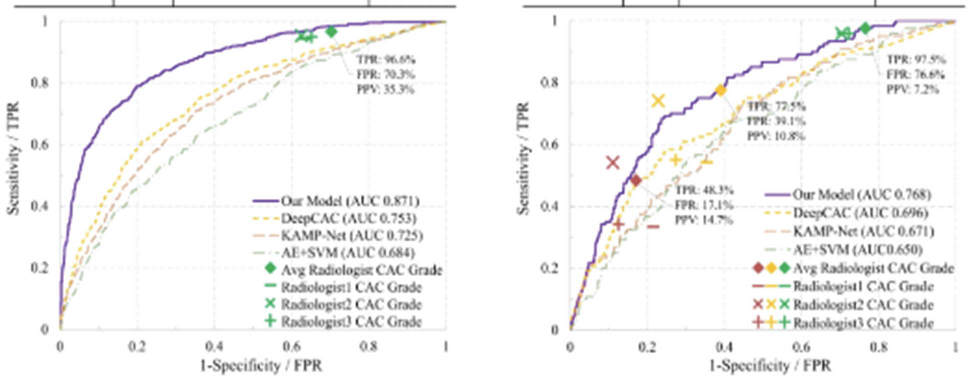

Fig. 7. Comparison of the proposed model with radiologist's performance in CVD detection of lung cancer.

Figure 7 depicts the ROC curves of multiple methods with respect to the TPR, FPR, and positive predictive value (PPV), where we have seen an escalated in TPR and FPR, and the declined PPV values exhibit that the proposed model has been improved compared to the existing models.

The proposed model achieved the AUC of 0.871 showing 95% confidence. The three stages included in Fig. 7(b) depict the performance of three different radiologists in comparison to the proposed model in CVD mortality prediction.

5. Conclusion

The primary objective of this study is to detect the VD deficiency using deep learning models. VD deficiency is one of the commonly found diseases worldwide that may lead to various chronic disorders. Moreover, vitamin testing from blood samples is time consuming and cost effective. Hence, this work focuses on detecting VD deficiency from noninvasive methods. By using this approach, VD levels in the body are calculated and the diet chart to improve the vital levels are designed. The detection accuracy of the proposed model is calculated and also compared with the existing models proving that this model is robust and efficient. The evaluation metrics used in this approach are precision, recall, accuracy. To perform this study, a custom dataset is curated from different individuals using sensors connected to them. The anthropogenic parameters like height, weight, muscle stretchability, bone fragility, and electrical activity of the brain are computed and analysed using the 8-layered deep learning model. The proposed model has the highest specificity and sensitivity. The AUC-ROC score of the proposed model is also shown to evaluate the model performance.

References

Al-Azhri, J, Y Zhang, W Bshara, G Zirpoli, SE McCann, T Khoury, CD Morrison, SB Edge, CB Ambrosone and S Yao (2017). Tumor Expression of vitamin D receptor and breast cancer histopathological characteristics and prognosis. *Clinical Cancer Research*, 23(1), 97–103.

Allahyari, E, P Hanachi, SJ Mirmoosavi, GA Ferns, A Bahrami and M Ghayour-Mobarhan (2021). Association between cardiometabolic risk factor and responsiveness to vitamin D supplementation: A new approach using artificial neural network analysis. *BMC Nutrition*, 7(1), 7.

Barrett, H and A McElduff (2010). Vitamin D and pregnancy: An old problem revisited. *Best Practice & Research Clinical Endocrinology & Metabolism*, 24(4), 527–539.

Bechrouri, S, A Monir, H Mraoui, EH Sebbar, E Saalaoui and M Choukri (2019). Performance of statistical models to predict vitamin D levels. In *Proceedings of the New Challenges in Data Sciences: Acts of the Second Conference of the Moroccan Classification Society*, pp. 1–4.

Bienertová-Vašků, J, F Zlámal, A Pohořalá, O Mikeš, M Goldbergová-Pávková, J Novák, Z Šplíchal and H Pikhart (2017). Allelic variants in vitamin D receptor gene are associated with adiposity measures in the central European population. *BMC Medical Genetics*, 18(1), 1–9.

Carretero, RG, L Vigil-Medina, O Barquero-Perez, I Mora-Jimenez, C Soguero-Ruiz and J Ramos-Lopez (2021). Machine learning approaches to constructing predictive models of vitamin D deficiency in a hypertensive population: A comparative study. *Informatics for Health and Social Care*, 46(4), 355–369.

Dede, H, O Takmaz, E Ozbasli, S Dede and M Gungor (2017). Higher level of oxidative stress markers in small for gestational age newborns delivered by cesarean section at term. *Fetal and Pediatric Pathology*, 36, 232–239.

DeLuca, GC, SM Kimball, J Kolasinski, SV Ramagopalan and GC Ebers (2013). The role of vitamin D in nervous system health and disease. *Neuropathology and Applied Neurobiology*, 39(5), 458–484.

de Oliveira, LF, LG de Azevedo, J da Mota Santana, LPC de Sales and M Pereira-Santos (2020). Obesity and overweight decreases the effect of vitamin D supplementation in adults: Systematic review and meta-analysis of randomized controlled trials. *Reviews in Endocrine and Metabolic Disorders*, 21(1), 67–76.

de Sire, A *et al.* (2022). Vitamin D deficiency in women with breast cancer: A correlation with osteoporosis? A machine learning approach with multiple factor analysis. *Nutrients*, 14(8), 1586.

Gagnon, C, ZX Lu, DJ Magliano, DW Dunstan, JE Shaw, PZ Zimmet, K Sikaris, PR Ebeling and RM Daly (2012). Low serum 25-hydroxyvitamin D is associated with increased risk of the development of the metabolic syndrome at five years: Results from a national, population-based prospective study (The Australian diabetes, obesity and lifestyle study: AusDiab). *The Journal of Clinical Endocrinology Metabolism*, 97(6), 1953–1961.

Gilbert-Diamond, D, A Baylin, M Mora-Plazas, C Marin, JE Arsenault, MD Hughes, WC Willett and E Villamor (2010). Vitamin D deficiency and anthropometric indicators of adiposity in school-age children: A prospective study. *The American Journal of Clinical Nutrition*, 92(6), 1446–1451.

Ginde, AA, MC Liu and CA Camargo (2009). Demographic differences and trends of vitamin D insufficiency in the US population, 1988–2004. *Archives of Internal Medicine*, 169(6), 626–632.

Gonoodi, K *et al.* (2019). An assessment of the risk factors for vitamin D deficiency using a decision tree model. *Diabetes & Metabolic Syndrome: Clinical Research Reviews*, 13(3), 1773–1777.

Goodwin, PJ, M Ennis, KI Pritchard, J Koo and N Hood (2009). Prognostic effects of 25-hydroxyvitamin D levels in early breast cancer. *Journal of Clinical Oncology*, 27(23), 3757–3763.

Chlebowski, RT (2013). Vitamin D and breast cancer incidence and outcome. *AntiCancer Agents in Medicinal Chemistry*, 13(1), 98–106.

Daubail, B *et al.* (2014). Association between serum concentration of vitamin D and 1-year mortality in stroke patients. *Cerebrovascular Diseases*, 37, 364–367.

Guo, S, RM Lucas, A-L Ponsonby and Ausimmune Investigator Group (2013). A novel approach for prediction of vitamin D status using support vector regression. *PloS One*, 8, e79970.

Hahn, S, U Haselhorst, S Tan, B Quadbeck, M Schmidt, S Roesler, R Kimmig, K Mann and OE Janssen (2006). Low serum 25-hydroxyvitamin D concentrations are associated with insulin resistance and obesity in women with polycystic ovary syndrome. *Experimental and Clinical Endocrinology Diabetes*, 114(10), 577–583.

Holick, MF and TC Chen (2008). Vitamin D deficiency: A worldwide problem with health consequences. *The American Journal of Clinical Nutrition*, 87(4), 1080S–1086S.

Hossain, S, MA Beydoun, HA Beydoun, X Chen, AB Zonderman and RJ Wood (2019). Vitamin D and breast cancer: A systematic review and meta-analysis of observational studies. *Clinical Nutrition ESPEN*, 30, 170–184.

Huss, L, ST Butt, S Borgquist, K Elebro, M Sandsveden, A Rosendahl and J Manjer (2019). Vitamin D receptor expression in invasive breast tumors and breast cancer survival. *Breast Cancer Research*, 21(1), 1–13.

Inaba, Y, JA Chen and SR Bergmann (2010). Prediction of future cardiovascular outcomes by flow-mediated vasodilatation of brachial artery: A meta-analysis. *International Journal of Cardiovascular Imaging*, 26, 631–640.

Jiang, H, DH Xiong, YF Guo, H Shen, P Xiao, F Yang, Y Chen, F Zhang, RR Recker and HW Deng (2007). Association analysis of vitamin D-binding protein gene polymorphisms with variations of obesity-related traits in Caucasian nuclear families. *International Journal of Obesity*, 31(8), 1319–1324.

Kamycheva, E, RM Joakimsen and R Jorde (2003). Intakes of calcium and vitamin D predict body mass index in the population of Northern Norway. *The Journal of Nutrition*, 133(1), 102–106.

Kazemian, E, A Amouzegar, ME Akbari, N Moradi, S Gharibzadeh, Y Jamshidi-Naeini, M Khademolmele, A As'habi and SH Davoodi (2019). Vitamin D receptor gene polymorphisms affecting changes in visceral fat, waist circumference and lipid profile in breast cancer survivors supplemented with vitamin D3. *Lipids in Health and Disease*, 18(1), 1–10.

Kim, C, SH Lee, JS Lim, Y Kim, MU Jang, MS Oh, S Jung, JH Lee, KH Yu and BC Lee (2020). Impact of 25-hydroxyvitamin D on the prognosis of acute ischemic stroke: Machine learning approach. *Frontiers in Neurology*, 11, 37.

LeBlanc, ES, JH Rizzo, KL Pedula, KE Ensrud, J Cauley, M Hochberg and TA Hillier (2012). Associations between 25-hydroxyvitamin D and weight gain in elderly women. *Journal of Women's Health*, 21(10), 1066–1073.

Li, HWR, RE Brereton, RA Anderson, AM Wallace and CKM Ho (2011). Vitamin D deficiency is common and associated with metabolic risk factors in patients with polycystic ovary syndrome. *Metabolism*, 60(10), 1475–1481.

Mahamat-Saleh, Y, D Aune and S Schlesinger (2020). 25-Hydroxyvitamin D status, vitamin D intake, and skin cancer risk: A systematic review and dose–response meta-analysis of prospective studies. *Scientific Reports*, 10, 13151.

Mai, X-M, Y Chen, CA Camargo Jr. and A Langhammer (2012). Cross sectional and prospective cohort study of serum 25-hydroxyvitamin D level and obesity in adults: The HUNT study. *American Journal of Epidemiology*, 175(10), 1029–1036.

Merlijn, T, KMA Swart, P Lips, MW Heymans, E Sohl, NM Van Schoor, CJ Netelenbos and PJM Elders (2018). Prediction of insufficient serum vitamin D status in older women: A validated model (2018). *Osteoporosis International*, 29(7), 1539–1547.

Mitri, J, MD Muraru and AG Pittas (2011). Vitamin D and type 2 diabetes: A systematic review. *European Journal of Clinical Nutrition*, 65, 1005–1015.

Mohamadkhani, A, A Katoonizadeh and H Poustchi (2015). Immune regulatory events in the clearance of HBsAg in chronic hepatitis B: Focuses on HLADP. *Middle East Journal of Digestive Diseases*, 7(1), 5.

Naureen, G, KM Sanders, L Busija, D Scott, K Lim, J Talevski, C Connaughton and SL Brennan-Olsen (2020). Prediction models and questionnaires developed to predict vitamin D status in adults: A systematic review. *Osteoporosis International*, 31(12), 2287–2302.

Nkembe, C-A, J Myara, G Helft and J Blacher (2009). Vitamine D etrisque cardiovasculaire. *Médecine des maladies Métaboliques*, 3, 247–250.

Ochs-Balcom, HM, R Chennamaneni, AE Millen, PG Shields, C Marian, M Trevisan and JL Freudenheim (2011). Vitamin D receptor gene polymorphisms are associated with adiposity phenotypes. *The American Journal of Clinical Nutrition*, 93(1), 5–10.

Park, KY *et al*. (2015). Serum vitamin D status as a predictor of prognosis in patients with acute ischemic stroke. *Cerebrovascular Disease*, 40, 73–80.

Perichart-Perera, O, V Avila-Sosa, JM Solis-Paredes, A Montoya-Estrada, E Reyes-Muñoz, AM Rodríguez-Cano, CP González-Leyva, M Sánchez-Martínez, G Estrada-Gutierrez and C Irles (2022). Vitamin D deficiency, excessive gestational weight gain, and oxidative stress predict small for gestational age newborns using an artificial neural network model. *Antioxidants*, 11(3), 574.

Ravani, P, F Malberti, G Tripepi, P Pecchini, S Cutrupi, P Pizzini, F Mallamaci and C Zoccali (2009). Vitamin D levels and patient outcome in chronic kidney disease. *Kidney International*, 75, 88–95.

Rojansky, N, A Brzezinski and JG Schenker (1992). Seasonality in human reproduction: An update. *Human Reproduction*, 7(6), 735–745.

Sohl, E, MW Heymans, RT de Jongh, M den Heijer, M Visser, T Merlijn, P Lips and NM van Schoor (2014). Prediction of vitamin D deficiency by simple patient characteristics. *The American Journal of Clinical Nutrition*, 99(5), 1089–1095.

Wang, L *et al*. (2012) Circulating 25-hydroxy-vitamin D and risk of cardiovascular disease: A meta-analysis of prospective studies. *Circulation: Cardiovascular Quality and Outcomes*, 5(6), 819–829.

Westermeier, F, PJ Sáez, R Villalobos-Labra, L Sobrevia and M Farías-Jofré (2014). Programming of fetal insulin resistance in pregnancies with maternal obesity by ER stress and inflammation. *BioMed Research International*, 2014, 917672.

Witham, M, F Dove, J Sugden, A Doney and A Struthers (2010). The effect of vitamin D replacement on markers of vascular health in stroke patients: A randomised controlled trial. *Nutrition, Metabolism and Cardiovascular Diseases*, 22, 864–870.

Xu, H, D-H Xiong, F-H Xu, Y-Y Zhang, S-F Lei and H-W Deng (2005). Association between VDR ApaI polymorphism and hip bone mineral density can be modified by body mass index: A study on postmenopausal Chinese women. *Acta Biochimica et Biophysica Sinica*, 37(1), 61–67.

Yalbuzdag, SA *et al*. (2015). Is 25(OH)D associated with cognitive impairment and functional improvement in stroke? A retrospective clinical study. *Journal of Stroke and Cerebrovascular Diseases*, 24, 1479–8610.

Ye, W-Z, AF Reis, D Dubois-Laforgue, CB Chantelot, J Timsit and G Velho (2001). Vitamin D receptor gene polymorphisms are associated with obesity in type 2 diabetic subjects with early age of onset. *European Journal of Endocrinology*, 145(2), 181–186.

Yildizhan, R, M Kurdoglu, E Adali, A Kolusari, B Yildizhan, HG Sahin and M Kamaci (2009). Serum 25-hydroxyvitamin D concentrations in obese and non-obese women with polycystic ovary syndrome. *Archives of Gynecology and Obstetrics*, 280(4), 559–563.

Zhang, H, G Yang and A Dong (2022). Prediction model between serum vitamin D and neurological deficit in cerebral infarction patients based on machine learning. *Computational and Mathematical Methods in Medicine*, 2022, 2914484.

Zhao, G, ES Ford, J Tsai, C Li and JB Croft (2012). Factors associated with vitamin D deficiency and inadequacy among women of childbearing age in the United States. *International Scholarly Research Notices*, 2012, 691486.