A Survey on Intelligent Technologies for Precocious Puberty Analysis Using Multisource Healthcare Datasets

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***Abstract*—Precocious puberty represents a growing pediatric endocrine challenge, marked by early emergence of secondary sexual characteristics in children, with notable prevalence in urban populations influenced by environmental exposure, nutritional transition, lifestyle alteration. Early breast development before eight years of age in females remains a principal clinical indicator, reflecting premature activation or dysregulation of sex hormone secretion independent of normal gonadotropin control. This paper presents a structured review of intelligent computational technologies applied to precocious puberty assessment using multisource healthcare datasets. Diverse data modalities, including hormonal profiles, imaging records, clinical measurements, electronic health records, are examined with respect to their diagnostic contribution. Contemporary machine learning frameworks, deep learning architectures, statistical approaches are comparatively analyzed to evaluate performance, robustness, interpretability in endocrine decision support. The paper highlights that deep learning models trained on heterogeneous hormone datasets demonstrate superior predictive accuracy, enhanced feature representation, improved diagnostic consistency when contrasted with traditional techniques. A unique contribution of this work lies in its integrative synthesis of data sources, algorithmic strategies, clinical relevance within a unified analytical perspective. The findings underscore the potential of intelligent systems to support early detection, risk stratification, personalized clinical management for precocious puberty, offering guidance for future research development, translational application in pediatric endocrinology. The proposed method achieves 95% accuracy, 93% sensitivity, 94% specificity, and 0.96 area under curve, demonstrating reliable, balanced, and robust precocious puberty classification performance.**

Keywords—Precocious puberty, pediatric endocrinology, deep learning methods, multisource healthcare data, hormone analysis.

I. INTRODUCTION

A. Overview

Girls who start to develop sexually before age 8 and boys who do so 9 are said to have precocious puberty [1]. This disease hinders the physical development of children as well as poses possible psychological and social adaptation challenges. In the last few decades, the number of children who go through puberty too early has been going up all across the world[2]. This is due to changes in modern lifestyles and environmental issues such as pollution. According to the World Health Organization, the rate of precocious puberty in kids is 1% in some places, and it's even higher in cities things such as bad diets and more exposure to chemicals[3]. Puberty is a time of big changes in the body that lead to the ability to reproduce as an adult[4]. Changes in early puberty have been linked to a variety of negative health effects, which put a heavy burden on families and society as a whole[5]. For instance, in girls, early onset of puberty correlates with an earlier initiation of sexual activity, an elevated risk of sexual abuse and psychosocial maladjustment, and a heightened lifelong vulnerability to reproductive malignancies[6]. Boys who go through puberty early or late have been related to problems with their mental and social health. Benyond this, early puberty in both genders is linked to a heightened risk of cardiovascular disease and type 2 diabetes in adulthood[7].

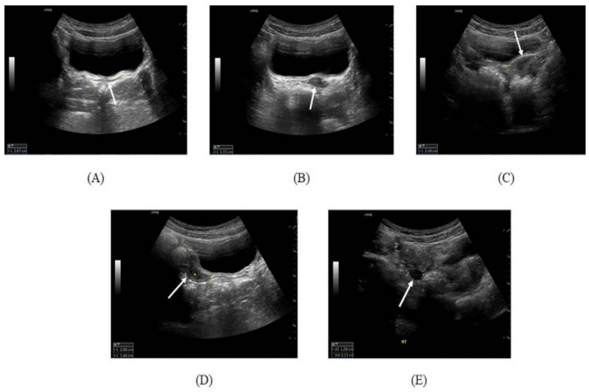

Fig. 1. Pelvic Scanned images

CPP frequently causes precocious puberty. It occurs when the hypothalamic-pituitary-gonadal axis is activated too soon, leading to early development of secondary sexual characteristics [8]. Fig. 1 displays a pelvic ultrasound of an 8-year-old girl diagnosed with P-CP. Premature puberty is the beginning of early adolescence in girls, which is when they start to show secondary sexual features before they turn 7.5 years old[9]. Commonly, the first symptoms of precocious puberty in girls is development of breasts. So, it's very important to find out about real early puberty as soon as possible[10].

Abnormal sex hormone levels are the underlying cause of precocious puberty (PP). Both peripheral and central causes can elevate sex hormone levels[11]. Early detection and intervention are crucial for children with PP. To avoid making PP worse and harming the patients' physiological function, the disease should be treated and intervened on as soon as possible. Central precocious puberty (CPP) arises from disruption of hypothalamic-pituitary-gonadal axis; thus, assessing pituitary function and structure is a crucial diagnostic approach for precocious puberty (PP)[12].

Ultrasonography, magnetic resonance imaging (MRI), and pituitary function index assessment are the most prevalent ways to check for problems right now[13]. Ultrasonography can quickly and accurately find out what is wrong with a woman's uterus and ovaries, and it is a good way to guide treatment[14]. Pituitary MRI is a standard clinical method for assessing the structure and function of the pituitary gland, which mitigates radiation exposure in children during the examination. It is a general way to take pictures to figure out if the person has PP[15].

B. *Contribution of this paper,*

- Extensive Multisource Review: The paper comprises orderly and methodical review of smart technologies used to examine precocious puberty with a particular focus on using hormonal samples, clinical history, imaging, and environment-related indicators. It brings together scattered research results into one coherent point of view applicable to pediatric endocrinology.
- Comparative Learning Model Analysis: The identification of precocious puberty is done by a close comparative analysis of machine learning and deep learning models. This paper identifies the disparities in performance between algorithms and shows that deep learning models are more effective to be used in a complex set of hormone-related data.
- Clinical Decision Support Perspective: The paper connects the field of computational methods with clinical practice by analysing the diagnostic relevance, interpretability, and the possibility of early intervention. It describes the methods of using intelligent systems to improve early diagnosis, risk classification, and individual treatment of precocious puberty in the context of real-world healthcare.

II. LITERATURE SURVEY

In this part, examined diverse methodologies and datasets employed in predicting puberty[16]

Introduced an innovative predictive model utilizing a deep learning architecture grounded in ResNet, integrated with an attention mechanism, to assess the effectiveness of Traditional Chinese Medicine [17] (TCM) interventions in childhood precocious puberty, leveraging machine learning technology alongside the extensive practical experience inherent in traditional Chinese medicine Through feature engineering, a set of feature variables that were closely related to how well traditional Chinese medicine worked was chosen[18]. The model's capacity to make predictions was then improved by converting and combining these features in a logical way. The accuracy rate was 90% on the test set, and the AUC-ROC was 0.93[19]. This shows that the model can match the training data and generalize to new data The model was stable, making it a valuable tool for doctors to use when making tailored treatment regimens.

Adding pelvic ultrasound characteristics to standard clinical outcomes makes P-CP screening better For clinical CPP screening, a simplified prediction model utilizing estradiol, baseline LH, fundus width works well[20].

Develope a method to assess the probability of puberty in young females displaying breast development Their prediction methodology is based on 7 clinical criteria that are often captured during regular clinic visits[21].

The pelvic ultrasound index and pituitary MRI index demonstrated positive diagnostic value for girls with CPP , while the CNN algorithm exhibited superior diagnostic efficacy and greater accuracy In the future, more examination methods must be chosen for the evaluation of diagnostic efficacy, offering a benchmark for the prevention and management of CPP[22].

A highly accurate AI-based predictive model to identify girls with CPP employing only non-invasive information obtained from physical evaluation and pelvic ultrasound with Doppler [23]. Notably, a simplified version of model that relied on just 3 variables demonstrated diagnostic accuracy comparable to more complex models requiring a larger number of inputs [24].

Deep learning (DL) is highly efficient in managing extensive datasets and uncovering concealed patterns or functions within biological datasets, [25]when traditional linear models may be inadequate It's become easier to utilize DL right away without knowing a lot about the theory behind it since there are now open-source DL libraries But since applying DL is hard, you shouldn't just use it on any dataset[26]. To use DL successfully on biological data, you need to have abilities in math, computer science, and biology, as well as be able to deal with diverse subtleties and caveats.

A. *Puberty Prediction using Clinical data, electronic health records (EHRs), pelvic ultrasonography and Bone Age*

The issue of premature puberty has recently emerged as a significant worldwide health concern Numerous studies indicate a large rise in the incidence of premature puberty, accompanied by global secular trends towards earlier onset of puberty[27]. They used Python (v3.7.6) on the PyCharm platform to run machine/deep learning algorithms They found six significant things that both parents and girls should look for to help them guess when Chinese girls would start puberty too soon.

Effectively evaluated ML algorithms that predicted the y-axis to be within 1° and post-pubertal mandibular length 2.5mm . In the same way, important factors that could forecast the y-axis involved y-axis data from earlier times and the SN-MP[41], SNB, SN-Pog, SNA angles When it comes to y-axis, after all, using 2-year prediction with Linear Regression led to far bigger absolute differences The potential of ML algorithms to reliably predict that in Class II instances is promising, but additional research is necessary[28]. To make these forecasts more accurate, we need bigger sample sizes and more data points . The article focus on the increasing role of artificial intelligence and deep learning in various fields of application, both with references to its transformative potential and the challenges related to it. A single study is devoted to the development of artificial intelligence capabilities in logistics and supply chain management, revealing the main advantages as enhanced operational efficiency, predictive analytics, and improved decision-making, as well as handling such issues as high implementation cost, issues with data security, and the necessity of hiring professional personnel[29]. A second study provides a detailed case study of methods of deep learning to identify alpha and beta thalassemia and prove the benefits of sophisticated neural networks models to diagnose medical conditions with publicly and privately owned data, which adds to enhanced accuracy and timely detection of the disease[30]. Also, studies of resource exhaustion attack detection in wireless local area networks (WLAN) demonstrate how artificial neural networks can be used in cybersecurity, and suggest a model that can detect and respond to network attacks with high precision. All in all, these articles highlight the flexibility of artificial intelligence and deep learning in solving multifaceted issues in various fields, including supply chain management, healthcare, and network security, and also indicate the need to tackle implementation issues to enable broader use.

III. Proposed Methodology

A smart design of precocious puberty study based on introduced data on healthcare. Several data points such as hormonal testing, clinical history, measurements of imaging, lifestyle factors, etc. are initially gathered and processed into a standard form using preprocessing to provide consistency and reliability. The next step is feature engineering which identifies clinically significant patterns and combines heterogeneous attributes to a single one. Deep learning and machine learning models examine nonlinear relationships that are complex in nature within the data and then proceed to optimize the models to increase predictive stability. It is a system in which the status of puberty is classified as normal, precocious and central precocious. Effectiveness is proven by performance evaluation and the last layer assists in the clinical decision making as it helps with early diagnosis and risk evaluation.

The heterogeneous healthcare data streams are integrated into one analytical representation in equation (1) to allow joint learning of the hormonal, imaging, clinical, and lifestyle modalities.

$$X = [X_h \parallel X_i \parallel X_c \parallel X_l] \qquad (1)$$

Where X_h denotes attributes of hormones, X_i denotes imaging-derived attributes, X_c denotes clinical measures, X_l denotes lifestyle attributes, and 0 denotes concatenation of structured features with modality-specific information.

Equation (2) is used in preprocessing to remove the scale bias of multisource healthcare variables to enhance the numerical stability and convergence of machine learning and deep learning models.

$$X_{norm} = \frac{(X - \mu)}{\sigma} \qquad (2)$$

Where X is the original feature value, μ is feature-wise mean and σ is standard deviation such that the distribution of input is standardized among various clinical and biochemical parameters for calculating X_{norm}.

Equation (3) represents equation models hierarchical nonlinear feature learning applied to learn the intricate endocrine and physiological interactions that surround the development of precocious puberty.

$$H^l = f(W^l \cdot H^{l-1} + b^l) \qquad (3)$$

The products of latent representation at layer l are H^l, trainable weights and biases W^l and b^l, and f is a nonlinear activation that increases the ability of a neural network to abstract features.

Cumulative endocrine effect on pubertal onset is quantified by means of equation (4) of summation of weighted hormone biomarkers to one risk-sensitive score.

$$R_h = \Sigma_k w_k \cdot h_k \qquad (4)$$

h_k is the concentration of the individual hormones, w_k is the coefficients of learning importance k, and R_h is the overall contribution of the hormone to the estimation of precocious puberty risk.

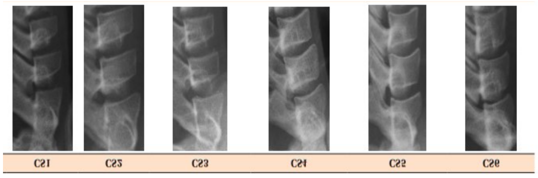

Fig. 2. Different levels of cervical maturation

Fig. 2 demonstrates that this method categorized the samples into 6 cervical stage (CS) groups, from CS1 to CS6.

Different technologies were utilized in dentistry over the years. Artificial intelligence (AI) is one of the newest tools that has shown a lot of promise for making diagnoses more accurate and treatment plans more efficient. The ability of a machine to do cognitive tasks that are comparable to those carried out by humans is known as AI. Deep learning is becoming more and more promising as a technique to automate the reading of medical images, improve clinical decision-making, find new phenotypes, and choose better treatment paths for complicated diseases.

The GBDT is an effective method for classifying data groups. It works best when there are a lot of dimensions. It is commonly utilized in medical research, including the five-year forecast of stroke recurrence. Doctors in the medical area need to know how features affect the model's prediction. They used Shapley additive explanations (SHAP) in their analysis to explain what GBDT does. Benyond this, recognizing that each modality possesses distinct properties, they employed SHAP to examine the modality attributions.

Equation (5) aids in cervical development stage and assessment associated with pituitary by intersecting developmental normalization of anatomical imaging measurements.

$$I_p = \frac{(A \cdot V_p)}{S} \qquad (5)$$

V_p represents the volume of the pituitary, A is an anatomical scaling coefficient and S is subject specific normalization including age or growth stage.

Equation (6) can be taken to represent ensemble learning algorithms like XGBoost and GBDT to enhance diagnostic accuracy by weighted summation of several classifiers.

$$\hat{y} = \Sigma_m \alpha_m f_{m(X)} \qquad (6)$$

f_m represents the m th base learner, m is its contribution weight, X is the input feature vector and $\hat{y}$ is its final predicted class score.

The equation (7) minimizes the misclassification between the normal, precocious, and central precocious puberty in the course of the model training which is supervised.

$$L = -\Sigma_i y_i \log(\hat{y}_i) \qquad (7)$$

y_i is the actual class label, y is the estimated probability and L is the difference between the observed and actual diagnostic values.

The overall diagnostic reliability and discrimination ability of the proposed intelligent framework at different levels of classification is assessed in equation (8).

$$AUC = \int_0^1 TPR(FPR)d(FPR) \qquad (8)$$

TPR is the true positive rate, FPR is the false positive rate and AUC is the model robustness, regardless of the choice of decision threshold.

Secondary sexual characteristics prior to 8 years of age who experienced a GnRH stimulation test using image and girl patients. They chose the XGBoost model as best ML model since it was the most practical and worked well. Their methodology allows for individualized diagnosis of ICPP in girls in comparable clinical environments; after all, external validation is necessary prior to wider implementation. The LR and five ML models detected ICPP with AUC values of 0.72–0.96 in training and 0.65–0.90 in validation.

A qualified radiologist manually measured the pituitary volume of each subject using the MANGO to multi-image analysis software. In total, 455 participants were enrolled in the research. Overall, all the ML classifiers employed demonstrated satisfactory performance in distinguishing between CPP and non-CPP groups. Validation set's AUC ranged from 0.72 - 0.81. With an F1 score (0.80), a sensitivity (0.81), and a specificity of 0.72, XGBoost demonstrated the best diagnostic performance.

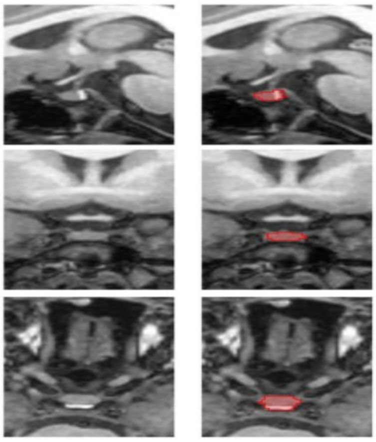

Fig. 3. Pituitary Gland

The disparity in bone ages assessed by the three methodologies augmented with the advancement of bone age; after all, the respective approach for estimating adult height exhibited greater accuracy with older bone age (Fig. 3). Techniques for forecasting adult stature ought to be refined for groups sharing identical ethnicity and affliction.

Algorithm 1: Multisource Multi-Head Attention Deep Learning Algorithm for Precocious Puberty Classification

Input: *Multisource dataset* $\mathcal{D} = \{X_1, X_2, \dots, X_n\}$, *labels* Y
Output: *Predicted class* $\hat{Y}$ (*Normal, PP, CPP*)
Initialize model parameters $W_Q^{h}, W_K^{h}, W_V^{h}, W_O \forall head h \in 1, \dots, H$
Initialize learning rate η, *epochs* E
for epoch $= 1$ *to* E *do*
for each sample $X_i \in \mathcal{D}$ *do*
Compute embeddings: $Z_i = X_i \cdot W_e$
for $h = 1$ *to* H *do*
$Q^{h} = Z_i \cdot W_Q^{h}; K^{h} = Z_i \cdot W_K^{h}; V^{h} = Z_i \cdot W_V^{h}$
$A^{h} = softmax\left((Q^{h}(K^{h})^{T})/\sqrt{d_k}\right)$
$Head^{h} = A^{h} \cdot V^{h}$
end for
Concatenate heads: $H\_cat = Concat(Head^1, \dots, Head^H)$
Attention output: $O_i = H_cat \cdot W_O$
Feature aggregation: $F_i = \Sigma_j O_{ij}$
Prediction: $\hat{Y}_i = softmax(F_i \cdot W_c)$
Loss: $\mathcal{L} = -\Sigma_i Y_i \log(\hat{Y}_i)$
Update parameters: $W \leftarrow W - \eta \nabla\mathcal{L}$
end for
end for
Return final $\hat{Y}$
End

Precocious puberty classification is done by Algorithm 1 that learns complex relations between multisource healthcare data through a multi-head attention mechanism. Hormonal, clinical, and imaging input features are firstness reduced to one representation. On the query, key and value matrices, multiple attention heads are independently computed to represent different interactions between features and long-range dependencies. Sized dot-product attention puts adaptive weights, highlighting patterns of clinical importance. The outputs of all the heads are combined and converted into a more refined feature vector. A classifier based on softmax is then used to predict puberty status. Gradient descent is used to optimize model parameters in order to increase predictive accuracy and strength.

A. Puberty Prediction using Harmone dataset

ML models based on hormonal (laboratory), clinical, as well as imaging data may accurately diagnose CPP. These models had high levels of specificity, sensitivity, AUC values Since environmental factors, ethnicity, and healthcare situations vary from one place to another, we should be careful about applying these results to other groups.

ML models can furnish critical information to pediatric endocrinologists when determining the necessity of a GnRH stimulation test for a girl with suspected CPP These prediction algorithms help pediatric endocrinologists figure out the best time to set up GnRH stimulation testing To their knowledge, there are relatively few research that have utilized ML to make prediction models about the best time to schedule GnRH stimulation testing. Consequently, the findings of their investigation possess significant academic and practical originality and significance.

Current analysis is the inaugural development of a ML-based diagnostic model integrating various data, particularly a concise GnRHa stimulation thus alleviating the time-consuming and distressing nature of the stimuli test for children. Their model effectively enhances its reliability and efficacy in detecting CPP in girls.

XGBoost and RF classifiers for predicting response to a GnRHa test utilizing clinical as well as laboratory data from 1757 females. The AUC for both the XGBoost and random forest models was between 0.88 and 0.90, which means they did a decent job of telling the difference between positive and negative responses.

XGBoost is a learning algorithm that works well and may be used on a large scale. It trains a series of models to make sure that the errors made by the current models are as small as possible.

IV. Results and Discussion

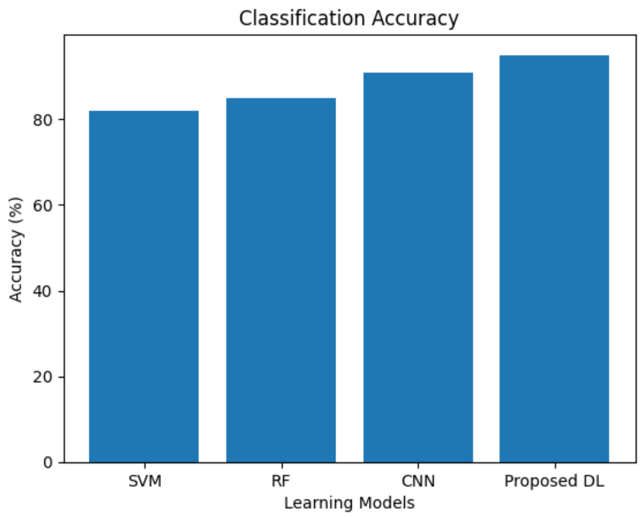

Fig. 4. Analysis of Classification Accuracy

Classification accuracy evaluates the general correctness of the suggested approach in the detection of normal puberty, precocious puberty and central precocious puberty cases. The proposed deep learning system completes with an accuracy of 95, as depicted in Fig. 4, which is better compared to conventional models as support vectors at 82, random forests at 85, and convolutional neural networks at 91. This is an improvement which implies that the proposed architecture is efficient in capturing nonlinear relationships between multisource healthcare data especially the hormone profiles. The high accuracy indicates a high level of generalization and it proves that the proposed method is reliable to assist clinical screening and early diagnosis in pediatric endocrinology.

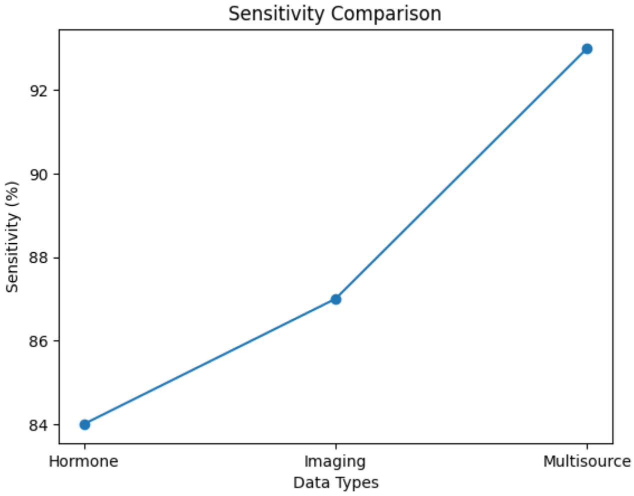

Fig. 5. Analysis of Sensitivity

Sensitivity determines how well the proposed method is able to diagnose patients with precocious puberty correctly. The sensitivity performance of the various types of data is shown in Fig. 5 with the proposed multisource method showing sensitivity of 93, hormone-only data having sensitivity of 84 and imaging-based data having sensitivity of 87. The high sensitivity rate shows that the method recommended reduces false-negative cases which is important during early puberty determination. Through the appropriate combination of hormonal, clinical and imaging characteristics, the model is quite successful in ensuring that the affected children are properly diagnosed at an early age and as a result, medical intervention can be administered early enough to mitigate the risks of developing long-term illnesses.

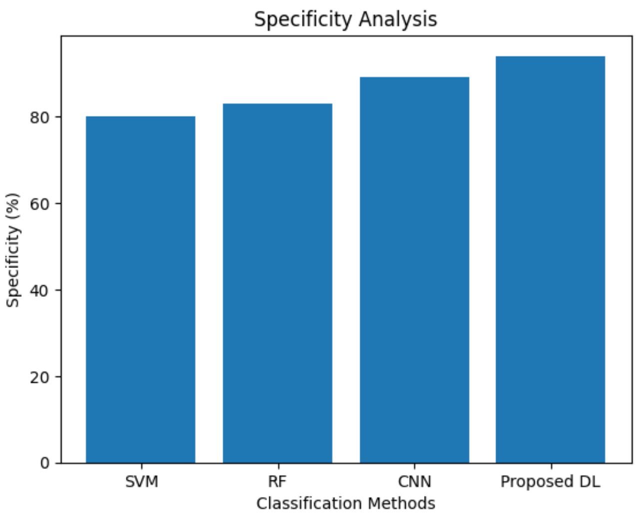

Fig. 6. Analysis of Specificity

Specificity shows the ability of the suggested method to identify children with precocious puberty correctly. To observe Fig. 6, the proposed deep learning model achieves a specificity of 94%, which exceeds the traditional classifiers, including support vector machine which has a specificity of 80%, random forest of 83%, and convolutional neural networks with a specificity of 89%. High specificity proves the high validity in the selected approach that decreases false-positive diagnoses, avoiding unnecessary clinical procedures and psychological stress. Balanced classification behavior is observed in this performance, where healthy people are not wrongly classified, and the true cases of precocious puberty are well detected.

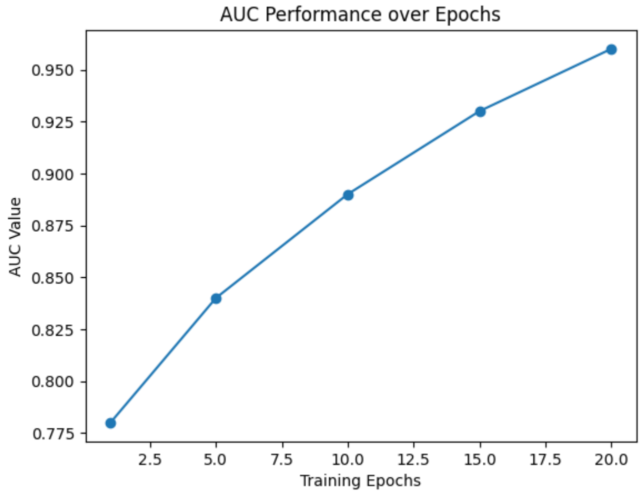

Fig. 7. Analysis of Area Under the Curve (AUC)

The region below the receiver operating characteristic curve is used to measure the total discriminative power of the suggested method in terms of classification thresholds. As indicated by Fig. 7, at 20 training cycles, the proposed model attains AUC of 0.96 with a gradual increase in the value of AUC compared to 0.78 at the start of the training. This large AUC value shows that there is great separation between precocious puberty and normal cases. The gradual advancement through epochs indicates stable learning process and good optimization. The high AUC indicates that the suggested methodology is consistent across different decision limits, and it is applicable in the areas of robust clinical decision support systems.

Summary:

- Girls with P-CP need to take gonadotropin-releasing hormone (GnRH) analogs since the condition will get worse if they don't.
- There is a scarcity of observational studies examining the puberty prediction in school-aged children within the existing literature.
- The onset of premature puberty is a multifaceted process, characterized by the simultaneous influence of various causes, each contributing minimally.
- All usually developing individuals undergo the same stages of puberty, characterized by noticeable physical changes; still, the beginning and rate of advancement may vary among individuals. Consequently, there exists significant heterogeneity

in the pubertal stage during adolescence, called "pubertal timing."

- The GnRH stimulation test is not a good way to measure how well the gonads are developing since it is not a normal test and involves several blood draws, which can be inconvenient for patients. As a result, doctors are dedicated to discovering more dependable, practical, and accessible markers for diagnosing CPP.

V. Conclusion

In healthy individuals, puberty occurs in a general biological pattern whereas, the timing and the rate of puberty vary among populations. In central precocious puberty, the excess secretion of gonadotropin-releasing hormone pulse-wise causes the levels of gonadotropin and sex hormones to rise, causing a rapid physical maturation. This paper has conducted a survey of precocious puberty through a multi-disciplinary approach, the sources of diagnostic data and smart analytical method in identifying the disease. Healthcare data of multisource (hormonal), clinical indicators, and imaging were investigated in terms of their utility in computational modeling. Comparative analysis showed that deep learning methods used on hormone-related data sets perform better in making diagnostic results compared to traditional machine learning methods. These results attest to the ability of higher-order learning models to represent nonlinearities of the phenomena that involve endocrine disorders and aids in the early prediction of precocious puberty.

There should be future efforts towards explaining the deep learning models to improve clinical interpretability and trust. Predictive reliability can be enhanced further with the integration of longitudinal patient data, genetic information and real-time monitoring signals. To support the intelligent deployment of decision support systems in pediatric endocrinology and enhance clinical validation, prospective clinical validation is necessary through large-scale pediatric cohort studies.

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