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Performance Evaluation via Error-based Goodness-of-fit Measures of a Newly Proposed Regression Model in Comparison with Twelve Existing Models

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Abstract

A comprehensive comparative evaluation of twelve existing simple regression models (Tangential, Sinuoidal, Square Root, Exponential, Power, Hyperbolic, Logarithmic, Polynomial, Quadratic, Linear, Cosinusoidal, and Cubic Root) versus a newly hybrid developed regression model using multiple error-based goodness-of-fit measures (Root Mean Squared Error, Mean Absolute Error, Mean Absolute Percentage Error, Symmetric Mean Absolute Percentage Error and Coefficient of Variation of Root Mean Squared Error) was conducted. The study focuses on scale-independent error behavior and predictive accuracy, which makes the evaluation more appropriate for modeling practical applications, unlike numerous past studies which relied much on coefficient of determination or information criteria measures. A developed model in this study consistently outperforms the twelve existing models in all chosen goodness-of-fit measures based on the empirical results from the two different datasets of programming performance and Physical Health Measurements of final year Computer Science students used. The non-parametric Friedman test also proves that the noted differences in the performance of the regression models are statistically significant, whereas the high value of Kendall coefficient of concordance shows that there is a high level of agreement between evaluation metrics. Hence, a combination of these outcomes gives strong statistical data of the effectiveness of the proposed model.

Keywords: Developed hybrid regression model; Error-based goodness-of-fit; Simple regression models; Performance evaluation; Model comparison.

1. Introduction

One of the well-known and used statistical methods is the regression analysis, which is employed to examine the associations between a response variable and one or more explanatory variables in a wide range of scientific disciplines, such as medicine, engineering, economics, and the biological/chemical sciences (*Ihekuna*, 2025; *Kutner et al.*, 2023). Its popularity is attributed to the fact that it is interpretable, it can be flexible, and it can model both linear and non-linear relationships. Nevertheless, a regression analysis is only as effective as the model that is formulated and the criteria applied to evaluate the performance of the model. Conventionally, summary statistics, particularly, the coefficient of determination (R^2) have been used extensively in model evaluation and comparison, particularly in the context of linear regression (*Chicco et al*., 2021). Though R^2 is useful in determining the extent of variability that is explained, it is not applicable in nonlinear regression scenarios where it is usually misleading (*Berk*, 2020; *Bartlett et al.*, 2020). The way the total variability is decomposed into explained and unexplained in nonlinear models is not the same as that of linear regression, making R^2 hard to interpret and inappropriate in model comparison, in certain cases (*Khan et al*., 2022; *Dünder*, 2021).

Other methods of model evaluation have been suggested to overcome these shortcomings. The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Hannan-Quinn Information Criterion (HQIC) are information-based selection criteria that were otherwise widely used to select a model, especially in likelihood-based models (*Haslbeck* & *van Bork*, 2024). Although these criteria are applicable to penalizing model complexity, they are in fact more suited to probabilistic model selection and not accurate model prediction. As such, they can be less useful in those applications where predictive performance and magnitude of error are of major concern. Error-based goodness-of-fit measures have been increasingly of interest in applied and experimental research in practical data analysis, where they are easily interpreted and directly related to prediction accuracy (*Duong* & *Lim*, 2023). The root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), symmetric mean absolute percentage error (SMAPE) and the coefficient of variation of root mean squared error (CV(RMSE)) are measures to assess the performance of a model in terms of the difference between the actual and predicted values (*Chicco et al*., 2021). These measures are especially powerful in nonlinear regression, because they are not based on the assumption of variance decomposition and the measurements are scale sensitive and scale free measures of model accuracy.

Recent research has highlighted the effectiveness of error-based measures as compared to conventional measures of goodness of fit between competing regression models, particularly in nonlinear and real-life data situations (*Chen* & *Chen*, 2020). RMSE and MAE are commonly known to quantify the overall prediction error whereas MAPE and SMAPE are used to interpret relative error and scale insensitivity. The CV(RMSE) especially is a normalized predictive error that is meaningfully comparable across models and datasets (*Maulud* & *Abdulazeez*, 2020). Although there are a lot of regression models which include simple linear models and complex nonlinear models like trigonometric, logarithmic, polynomials and power-based models, none of the models performs perfectly in all the datasets. The suitability of a model can be determined by the underlying data structure, distributional characteristics and functional relationships of the variables of interest (*Algamal*, 2019; *Taher*, 2025). This has encouraged further studies on formulation of new regression formulations, which can provide better degree of flexibility and predictive performance.

It is against this background that the current study formulates a new regression model and carries out a full comparative performance analysis to twelve existing regression models, i.e. Tangential, Sinuoidal, Square Root, Exponential, Power, Hyperbolic, Logarithmic, Polynomial, Quadratic, Linear, Cosinusoidal, and Cubic Root models. In contrast to other research works, which mainly use information-based criteria, the current study uses five error-based goodness-of-fit measures, namely, RMSE, MAE, MAPE, SMAPE, and CV(RMSE) to measure and compare model results. The fact that the study concentrated on predictive accuracy and error behavior, offers a more practical meaning evaluation framework on nonlinear regression modeling.

2. Materials and Methods

2.1 Regression Models

Twelve simple regression models are considered in this study. These include Tangential, Sinusoidal, Square Root, Exponential, Power, Hyperbolic, Logarithmic, Polynomial, Quadratic, Linear, Cosinusoidal and Cubic-Root models, as specified in Equations (1)–(12) respectively.

$$Z = \phi_0 + \phi_1 \tan(W) + \varepsilon \tag{1}$$

$$Z = \phi_0 + \phi_1 Sin(W) + \varepsilon \tag{2}$$

$$Z = \phi_0 + \phi_1 \sqrt{W} + \varepsilon \tag{3}$$

$$Z = \phi_0 + \exp(\phi_1 W) + \varepsilon \tag{4}$$

$$Z = \phi_0 W^{\phi_1} + \varepsilon \tag{5}$$

$$Z = \phi_0 + \phi_1 (1/W) + \varepsilon \tag{6}$$

$$Z = \phi_0 + \phi_1 \ln(W) + \varepsilon \tag{7}$$

$$Z = \phi_0 + \phi_1 W + \phi_2 W^2 + \phi_3 W^3 + \varepsilon \tag{8}$$

$$Z = \phi_0 + \phi_1 W + \phi_2 W^2 + \varepsilon \tag{9}$$

$$Z = \phi_0 + \phi_1 W + \varepsilon \tag{10}$$

$$Z = \phi_0 + \phi_1 \cos(W) + \varepsilon \tag{11}$$

$$Z = \phi_0 + \phi_1 W^{1/3} + \varepsilon \tag{12}$$

2.2 Developed Hybrid Regression Model

The developed hybrid regression model was a combination of hyperbolic, reciprocal of square root and logarithmic models and it is presented in Equation (13). Thus, the least squares technique is employed to estimate the parameters via minimizing the error sum of squares between the observed value and its predicted value.

$$Z = \phi_0 + \frac{\phi_1}{W} + \frac{\phi_2}{\sqrt{W}} + \phi_3 \ln(W) + \varepsilon \tag{13}$$

The error $(e) = Z - \hat{Z}$ (13a)

$$\hat{Z} = \hat{\phi}_0 + \frac{\hat{\phi}_1}{W} + \frac{\hat{\phi}_2}{\sqrt{W}} + \hat{\phi}_3 \ln(W)$$

If n pairs of observation of a sample are $(W_1, Z_1),(W_2, Z_2),\cdots(W_n, Z_n)$, then we obtain:

$$Z_i = \phi_0 + \frac{\phi_1}{W_i} + \frac{\phi_2}{\sqrt{W_i}} + \phi_3 \ln(W_i) + \varepsilon_i,\ for\ i = 1,2,3,\cdots n \tag{14}$$

V is minimized by seeking for the estimators $\hat{\phi}_0$, $\hat{\phi}_1$, $\hat{\phi}_2$ and $\hat{\phi}_3$ of ϕ_0, ϕ_1, ϕ_2, and ϕ_3 respectively;

$$Let\ V = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} \left(Z_i - \hat{\phi}_0 - \frac{\hat{\phi}_1}{W_i} - \frac{\hat{\phi}_2}{\sqrt{W_i}} - \hat{\phi}_3 \ln(W_i) \right)^2 \tag{15}$$

Differentiate Equation (15) partially w.r.t. $\hat{\phi}_0$, $\hat{\phi}_1$, $\hat{\phi}_2$ and $\hat{\phi}_3$, equate to zero to obtain Equations (16), (17), (18) and (19) as normal equations.

$$\frac{\partial V}{\partial \hat{\phi}_0} = -2 \sum_{i=1}^{n} \left(Z_i - \hat{\phi}_0 - \frac{\hat{\phi}_1}{W_i} - \frac{\hat{\phi}_2}{\sqrt{W_i}} - \hat{\phi}_3 \ln(W_i) \right) = 0$$

$$\Rightarrow n\hat{\phi}_0 + \hat{\phi}_1 \sum_{i=1}^{n} \frac{1}{W_i} + \hat{\phi}_2 \sum_{i=1}^{n} \frac{1}{\sqrt{W_i}} + \hat{\phi}_3 \sum_{i=1}^{n} \ln(W_i) = \sum_{i=1}^{n} Z_i \tag{16}$$

$$\frac{\partial V}{\partial \hat{\phi}_1} = -2 \sum_{i=1}^{n} \frac{1}{W_i} \left(Z_i - \hat{\phi}_0 - \frac{\hat{\phi}_1}{W_i} - \frac{\hat{\phi}_2}{\sqrt{W_i}} - \hat{\phi}_3 \ln(W_i) \right) = 0$$

$$\Rightarrow \hat{\phi}_0 \sum_{i=1}^{n} \frac{1}{W_i} + \hat{\phi}_1 \sum_{i=1}^{n} \frac{1}{W_i^2} + \hat{\phi}_2 \sum_{i=1}^{n} \frac{1}{W_i^{\frac{3}{2}}} + \hat{\phi}_3 \sum_{i=1}^{n} \frac{\ln(W_i)}{W_i} = \sum_{i=1}^{n} \frac{Z_i}{W_i} \quad (17)$$

$$\frac{\partial V}{\partial \hat{\phi}_2} = -2 \sum_{i=1}^{n} \frac{1}{\sqrt{W_i}} \left(Z_i - \hat{\phi}_0 - \frac{\hat{\phi}_1}{W_i} - \frac{\hat{\phi}_2}{\sqrt{W_i}} - \hat{\phi}_3 \ln(W_i) \right) = 0$$

$$\Rightarrow \hat{\phi}_0 \sum_{i=1}^{n} \frac{1}{\sqrt{W_i}} + \hat{\phi}_1 \sum_{i=1}^{n} \frac{1}{W_i^{\frac{3}{2}}} + \hat{\phi}_2 \sum_{i=1}^{n} \frac{1}{W_i} + \hat{\phi}_3 \sum_{i=1}^{n} \frac{\ln(W_i)}{\sqrt{W_i}} = \sum_{i=1}^{n} \frac{Z_i}{\sqrt{W_i}} \quad (18)$$

$$\frac{\partial V}{\partial \hat{\phi}_3} = -2 \sum_{i=1}^{n} \ln(W_i \left(Z_i - \hat{\phi}_0 - \frac{\hat{\phi}_1}{W_i} - \frac{\hat{\phi}_2}{\sqrt{W_i}} - \hat{\phi}_3 \ln(W_i) \right) = 0$$

$$\Rightarrow \hat{\phi}_0 \sum_{i=1}^{n} \ln(W_i) + \hat{\phi}_1 \sum_{i=1}^{n} \frac{\ln(W_i)}{W_i} + \hat{\phi}_2 \sum_{i=1}^{n} \frac{\ln(W_i)}{\sqrt{W_i}} + \hat{\phi}_3 \sum_{i=1}^{n} \left[\ln(W_i)\right]^2 = \sum_{i=1}^{n} Z_i \ln(W_i) \quad (19)$$

Equations (16), (17), (18) and (19) are written in matrix form as;

$$\begin{pmatrix} n & \sum_{i=1}^{n} \frac{1}{W_i} & \sum_{i=1}^{n} \frac{1}{\sqrt{W_i}} & \sum_{i=1}^{n} \ln(W_i) \\ \sum_{i=1}^{n} \frac{1}{W_i} & \sum_{i=1}^{n} \frac{1}{W_i^2} & \sum_{i=1}^{n} \frac{1}{W_i^{3/2}} & \sum_{i=1}^{n} \frac{\ln(W_i)}{W_i} \\ \sum_{i=1}^{n} \frac{1}{\sqrt{W_i}} & \sum_{i=1}^{n} \frac{1}{W_i^{3/2}} & \sum_{i=1}^{n} \frac{1}{W_i} & \sum_{i=1}^{n} \frac{\ln(W_i)}{\sqrt{W_i}} \\ \sum_{i=1}^{n} \ln(W_i) & \sum_{i=1}^{n} \frac{\ln(W_i)}{W_i} & \sum_{i=1}^{n} \frac{\ln(W_i)}{\sqrt{W_i}} & \sum_{i=1}^{n} \left[\ln(W_i)\right]^2 \end{pmatrix} \begin{pmatrix} \hat{\phi}_0 \\ \hat{\phi}_1 \\ \hat{\phi}_2 \\ \hat{\phi}_3 \end{pmatrix} = \begin{pmatrix} \sum_{i=1}^{n} Z_i \\ \sum_{i=1}^{n} \frac{Z_i}{W_i} \\ \sum_{i=1}^{n} \frac{Z_i}{\sqrt{W_i}} \\ \sum_{i=1}^{n} Z_i \ln(W_i) \end{pmatrix}$$

$$\therefore \begin{pmatrix} \hat{\phi}_0 \\ \hat{\phi}_1 \\ \hat{\phi}_2 \\ \hat{\phi}_3 \end{pmatrix} = \begin{pmatrix} n & \sum_{i=1}^{n} \frac{1}{W_i} & \sum_{i=1}^{n} \frac{1}{\sqrt{W_i}} & \sum_{i=1}^{n} \ln(W_i) \\ \sum_{i=1}^{n} \frac{1}{W_i} & \sum_{i=1}^{n} \frac{1}{W_i^2} & \sum_{i=1}^{n} \frac{1}{W_i^{3/2}} & \sum_{i=1}^{n} \frac{\ln(W_i)}{W_i} \\ \sum_{i=1}^{n} \frac{1}{\sqrt{W_i}} & \sum_{i=1}^{n} \frac{1}{W_i^{3/2}} & \sum_{i=1}^{n} \frac{1}{W_i} & \sum_{i=1}^{n} \frac{\ln(W_i)}{\sqrt{W_i}} \\ \sum_{i=1}^{n} \ln(W_i) & \sum_{i=1}^{n} \frac{\ln(W_i)}{W_i} & \sum_{i=1}^{n} \frac{\ln(W_i)}{\sqrt{W_i}} & \sum_{i=1}^{n} \left[\ln(W_i)\right]^2 \end{pmatrix}^{-1} \begin{pmatrix} \sum_{i=1}^{n} Z_i \\ \sum_{i=1}^{n} \frac{Z_i}{W_i} \\ \sum_{i=1}^{n} \frac{Z_i}{\sqrt{W_i}} \\ \sum_{i=1}^{n} Z_i \ln(W_i) \end{pmatrix} \quad (20)$$

2.3 Measures via Goodness-of-Fit

Since Z_i denotes the value observed for the response variable while the predicted value gotten via a regression model denotes $\hat{Z}_i$, then the errors are defined as in Equation (13a). Thus, smaller values of Equations (21) to (25) indicate better model fit.

2.3.1 Root Mean Squared Error (RMSE)

RMSE is given mathematically as;

$$RMSE = \frac{1}{n} \sum_{i=1}^{n} e_i^2 = \left(\frac{1}{n} \sum_{i=1}^{n} (Z_i - \hat{Z}_i)^2 \right)^{\frac{1}{2}} \quad (21)$$

2.3.2 Mean Absolute Error (MAE)

MAE is given mathematically as;

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Z_i - \hat{Z}_i\right| \tag{22}$$

2.3.3 Mean Absolute Percentage Error (MAPE)

MAPE is given mathematically as;

$$MAE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{Z_i - \hat{Z}_i}{Z_i}\right| \tag{23}$$

2.3.4 Symmetric Mean Absolute Percentage Error (SMAPE)

SMAPE is given mathematically as;

$$SMAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{\left|Z_i - \hat{Z}_i\right|}{\left(\left|Z_i\right| + \left|\hat{Z}_i\right|\right)/2} \tag{24}$$

2.3.5 Coefficient of Variation of RMSE [CV(RMSE)]

CV(RMSE) is given mathematically as;

$$RMSE = \frac{RMSE}{\bar{Z}} \times 100 \tag{25}$$

2.4 RStudio Programming Scripts for Estimation of Simple Regression Models

The RStudio programming scripts were written to estimate the parameters of the simple regression models of Equations (1) – (12), as well as the self-developed simple regression model in Equation (13), and also, the goodness-of-fit measures. The scripts are as shown below:

```
# DATA
# Load the data
rm(Z, W)
data <- read.csv(file.choose())
attach(data)
Z=c(Z)
W=c(W)
n <- length(Z)
# Definition of the Regression Equations
md1  <- lm(Z ~ I(tan(W)))
md2  <- lm(Z ~ I(sin(W)))
md3  <- lm(Z ~ I(sqrt(W)))
md4  <- nls(Z ~ ϕ0 + exp(ϕ1*W), start=list(ϕ0=1, ϕ1=0.01))
md5  <- nls(Z ~ ϕ0*W^ ϕ1, start=list(ϕ0=1, ϕ1=1))
md6  <- lm(Z ~ I(1/W))
md7  <- lm(Z ~ I(log(W)))
md8  <- lm(Z ~ W + I(W^2) + I(W^3))
md9  <- lm(Z ~ W + I(W^2))
md10 <- lm(Z ~ W)
md11 <- lm(Z ~ I(cos(W)))
md12 <- lm(Z ~ I(W^(1/3)))
md13 <- lm(Z ~ I(1/W) + I(1/sqrt(W)) + I(log(W)))
models <- list(
  Tangent=md1, Sinusoidal=md2, Sqrt=md3, Exponential=md4, Power=md5,
```

```
  Hyperbolic=md6, Logarithmic=md7, Polynomial=md8, Quadratic=md9,
  Linear=md10, Cosinusoidal=md11, CubicRoot=md12, Proposed=md13
)
# Measures via Goodness-Of-Fit
gof <- function(model){
  z_hat <- fitted(model)
  res <- Z - z_hat
  rmse <- sqrt(mean(res^2))
  mae <- mean(abs(res))
  mape <- mean (abs(res / Z)) * 100
  smape <- mean(2 * abs(res) / (abs(Z) + abs(z_hat))) * 100
  cv_rmse <- (rmse / mean(Z)) * 100
  return(c(RMSE=rmse, MAE=mae, MAPE=mape, SMAPE=smape, CV_RMSE=cv_rmse))
}
# EXTRACT PARAMS & FIT MEASURES
max_coef <- max(sapply(models, function(x) length(coef(x))))
# Initialize empty data frame
combined_table <- data.frame(Model=names(models))
# Add coefficient columns
for(i in 1:max_coef){
  combined_table[[paste0("Beta",i-1)]] <- NA
}
# Add goodness-of-fit columns
combined_table$RMSE <- NA
combined_table$MAE <- NA
combined_table$MAPE <- NA
combined_table$SMAPE <- NA
combined_table$CV_RMSE <- NA

# Fill the table
for(i in 1:length(models)){
  coefs <- coef(models[[i]])
  combined_table[i, paste0("Beta",0:(length(coefs)-1))] <- coefs
  combined_table[i, c("RMSE","MAE","MAPE","SMAPE","CV_RMSE")] <- gof(models[[i]])
}
# Round numeric values for readability
combined_table[,-1] <- round(combined_table[,-1], 4)
# OUTPUT TABLE
print(combined_table)
```

2.5 Data Collection

Two different datasets were obtained from 100 purposively selected final year computer science students from selected Universities in South-South Nigeria. The first dataset was on programming performance of students, with the dependent variable (Z_1) as score (%) in a programming course and the independent variable (W_1) as number of hours spent coding per week. The second dataset was on physical health measurements of the same final year computer science students, with the dependent variable (Z_2) pulse rate and the independent variable (W_2) weight. The data were presented in Table 1.

Table 1. Dataset on Programming Performance and Physical Health Measurements of Final Year Computer Science Students

S/N	Z_1	W_1	Z_2	W_2	S/N	Z_1	W_1	Z_2	W_2	S/N	Z_1	W_1	Z_2	W_2	S/N	Z_1	W_1	Z_2	W_2
1	48	4	51	58.5	26	77	13	49	57.2	51	65	8	63	70.5	76	52	4	51	58.4
2	58	8	54	61.6	27	67	10	55	63.1	52	57	4	58	66.1	77	68	9	54	61.6
3	70	12	58	51.1	28	48	3	54	61.3	53	53	5	48	56.1	78	61	5	58	51.1
4	70	12	53	61.2	29	69	12	58	66.2	54	83	10	51	59.2	79	44	4	53	61.2
5	53	9	59	66.3	30	70	12	62	69.4	55	81	13	53	50.1	80	71	15	59	66.3
6	58	6	53	61.3	31	73	14	58	66.1	56	70	15	52	60.2	81	62	7	53	61.2
7	47	5	83	91.1	32	66	11	62	69.4	57	44	4	52	59.9	82	60	7	83	91.1
8	70	9	57	65.2	33	54	5	59	66.3	58	72	11	54	61.4	83	69	11	57	65.2
9	62	9	66	73.3	34	72	16	53	61.2	59	68	10	61	69.2	84	71	5	66	73.3
10	58	4	67	74.7	35	80	15	53	61.1	60	77	11	51	58.4	85	63	7	67	74.7
11	52	7	55	62.3	36	55	6	66	73.4	61	58	6	49	56.3	86	82	14	55	62.3
12	57	6	63	70.5	37	68	9	70	77.6	62	48	4	47	54.7	87	80	16	63	70.5
13	54	4	58	66.1	38	63	8	62	70.1	63	49	5	48	56.2	88	52	4	58	66.1
14	60	9	48	56.1	39	61	7	68	76.2	64	66	13	53	61.1	89	72	11	48	56.1
15	78	13	51	59.2	40	77	14	51	58.4	65	84	16	49	57.2	90	75	13	51	59.2
16	80	15	53	50.1	41	64	8	54	61.6	66	83	13	55	63.1	91	64	8	58	66.2
17	50	7	52	60.2	42	52	4	58	51.1	67	59	8	54	61.3	92	50	5	62	69.4
18	49	4	52	59.9	43	73	12	53	61.2	68	68	13	58	66.2	93	84	14	58	66.2
19	80	13	54	61.4	44	69	10	59	66.3	69	76	14	59	66.3	94	92	16	62	69.4
20	61	6	61	69.4	45	56	5	53	61.2	70	64	9	53	61.2	95	71	12	59	66.6
21	44	3	51	58.4	46	71	14	83	91.1	71	71	16	53	61.1	96	57	9	53	61.5
22	62	13	49	56.3	47	67	11	57	65.2	72	52	4	66	73.4	97	78	14	66	72.2
23	70	11	47	54.7	48	62	6	66	73.3	73	86	15	70	77.6	98	49	6	68	74.9
24	59	7	48	56.2	49	70	13	67	74.7	74	44	3	62	70.1	99	64	8	56	62.5
25	81	14	53	61.1	50	76	15	55	62.3	75	56	5	68	76.2	100	78	11	64	70.6

3. Results and Discussion

The data collected for this study were analyzed with the aid of RStudio 2025.9.1.0 version to estimate the parameters of the simple regression models, as well as the self-developed model, in addition with five error-based goodness-of-fit measures for the two different datasets, as displayed in Tables 2 and 3.

Table 2. Programming Performance Dataset Results for Simple Regression Models

Models	Coefficients of Regression				Goodness-of-fit Measures				
	$\hat{\phi}_0$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\phi}_3$	RMSE	MAE	MAPE	SMAPE	CV (RMSE)
Tangential	64.4252	-0.0284			11.1169	9.2133	14.9177	14.3928	17.1187
Sinusoidal	65.0970	4.8600			10.7108	9.2350	14.8776	14.4216	16.4934
Square root	20.9171	14.7738			5.3125	4.0342	6.3087	6.2568	8.1806
Exponential	54.2233	0.2172			6.7395	5.4275	8.7238	8.5361	10.3780
Power	31.5826	0.3328			5.3298	4.0365	6.3039	6.2541	8.2072
Hyperbolic	83.0676	-135.1700			6.1765	4.8359	7.6652	7.6162	9.5111
Logarithmic	21.0365	20.6226			5.4284	4.0939	6.3834	6.3331	8.3592
Polynomial	37.1983	3.5358	-0.0399	-0.0009	5.3112	4.0584	6.3520	6.3010	8.1787
Quadratic	36.6247	3.7645	-0.0664		5.3114	4.0539	6.3447	6.2934	8.1789
Linear	41.5205	2.5101			5.3803	4.1256	6.4782	6.4163	8.2850
Cosinusoidal	64.9599	0.9937			11.2307	9.4595	15.3344	14.7603	17.2939
Cubic root	0.3108	31.3957			5.3296	4.0369	6.3046	6.2542	8.2070
Self-Developed	-315.5884	-345.0491	650.1951	91.9919	5.3035	4.0328	6.3037	6.2481	8.1668

Table 2 shows the regression coefficients, and the measures of goodness of fit of the Programming Performance dataset using twelve available simple regression models and the self-formulated (proposed) model. This self-constructed model has the least values in RMSE (5.3035), MAE (4.0328), MAPE (6.3037), SMAPE (6.2481) and CV-RMSE (8.1668), where it fits best of all the other considered models. The next best performing model is the Square Root model which has the MAE (4.0342), MAPE (6.3087) and SMAPE (6.2568), however it is a bit less precise than the self-developed model. The regression coefficients of the self-developed model (ϕ_0 = -315.5884, ϕ_1 = -345.0491, ϕ_2 = 650.1951, and ϕ_3 = 91.9919) show the capability of the model to explain both linear and nonlinear correlations between hours spent coding and programming performance. To identify the best regression model the error based measures of goodness of fit of every statistic in all the models were ranked and a total rank of each model was calculated to identify the best performing model. These rankings are provided in Table 3.

Table 3. Goodness-of-fit Measures' Ranks for Programming Performance Dataset

	Ranks						
Models	**RMSE**	**MAE**	**MAPE**	**SMAPE**	**CV (RMSE)**	**Total Rank**	**Position**
Tangential	12	11	12	11	12	58	12
Sinusoidal	11	12	11	12	11	57	11
Square root	4	2	4	4	4	18	2
Exponential	10	10	10	10	10	50	10
Power	6	3	2	2	6	19	3
Hyperbolic	9	9	9	9	9	45	9
Logarithmic	8	7	7	7	8	37	7
Polynomial	2	6	6	6	2	22	6
Quadratic	3	5	5	5	3	21	5
Linear	7	8	8	8	7	38	8
Cosinusoidal	13	13	13	13	13	65	13
Cubic root	5	4	3	3	5	20	4
Self-Developed	1	1	1	1	1	5	1

Table 3 shows the ranking of the twelve available simple regression models and the self-developed model in terms of the five error-based goodness-of-fit measures: RMSE, MAE, MAPE, SMAPE, and CV-RMSE. All the models were ranked in terms of each measure with the lowest number representing the best and the progressive numbers representing the worst performance. The overall rank is the sum of ranks in all five criteria and position column is the total rank in terms of performance. The model developed by the self-ranks on the first place in all of the five goodness-of-fit measures, and its overall rank is 5, which is an obvious demonstration of its superiority over the rest of the models and that it fits better to the Programming Performance dataset on the whole. The square root model is followed with the next-best performing model of total rank 18, and the Power model and the Cubic root model also demonstrate the competitive performance with the total rank of 19 and 20 respectively.

The mid-level positions are taken by Polynomial, Quadratic, and Logarithmic models that represent the moderate performance. Models like Cosinusoidal, Tangential as well as Sinuoidal models have been found to be poor models as they rank lowest in nearly all the criteria which imply that they are not the most appropriate models to model this data. The ranking methodology gives a strong and detailed evaluation of the model performance by adopting various measures of an error at the same time and also points out the effectiveness and strength of the self-built regression model as the best model to predict the results in this data.

However, it was ideal to examine the claim statistically by carrying out a statistical test. Hence, the Friedman technique was adopted, and the results are summarized in Table 4, and the hypotheses are stated thus:

Hypotheses One

H_0: The performance of all the simple regression models is the same (Equal median ranks)

H_1: At least one of the simple regression models significantly performs differently

Table 4. Results of Friedman Test for Goodness-of-fit Measures' Ranks for Programming Performance Dataset

Statistic	Value
Number of Regression Models (Treatment)	13
Number of Goodness-of-fit Measures (Blocks)	5
Friedman Chi-square (χ^2)	56.52
DF	12
p-value	0.000
Kendall's Coefficient of Concordance (W)	0.95
Decision	Reject H_0

The results of the Friedman test in Table 4 tested hypothesis one whether the difference in the performance of the simple regression models is significant statistically as measured by ranked goodness of fit measures of the Programming Performance Dataset. The null hypothesis (H_0) is that the different regression models are equally ranked with respect to the median, and hence the models are not different in performance whereas the alternative hypothesis (H_1) is that at least one of the regression models is distinctly different. The Friedman test indicates Friedman chi-square = 56.52 with 12 degrees of freedom and a p-value=0.000 which is much lower than the 0.05 level of significance or significance test. This gives a good statistical indication to disregard the null hypothesis.

Therefore, the dataset does not indicate that all simple regression models yield equal results as the assumption implies. In addition, the coefficient of concordance (W = 0.95) of Kendall shows that there is a very high degree of agreement between the goodness-of-fit measures (RMSE, MAE, MAPE, SMAPE, and CV-RMSE) in ranking regression models. This high concordance ascertains the fact that the differences in model performance observed are consistent in all the measures used in the evaluation and do not depend on one measure. In general, as the Friedman test outcomes indicate, at least one of the regression models has a significant high prediction success rate compared to the others with regards to the Programming Performance Dataset. This result statistically confirms the comparative analysis and is an adequate foundation to define the model with the largest performance, which, as it is indicated in the previous ranking tables, is the self-developed regression model.

Table 5: Physical Health Measurements Dataset Results for Simple Regression Models

Models	Coefficients of Regression				Goodness-of-fit Measures				
	$\hat{\phi}_0$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\phi}_3$	RMSE	MAE	MAPE	SMAPE	CV (RMSE)
Tangential	57.4930	0.0108			7.3732	5.6767	9.6763	9.6989	12.8230
Sinusoidal	57.8290	2.1062			7.2370	5.3748	9.1497	9.1652	12.5862
Square root	-54.9263	14.0110			2.9051	1.7283	3.0614	3.1552	5.0524
Exponential	41.2835	0.0421			2.6236	2.0913	3.6660	3.6694	4.5628
Power	0.9279	0.9899			2.7136	1.5223	2.7291	2.8164	4.7192
Hyperbolic	113.1073	-3543.2175			3.6168	2.2775	3.9504	4.0838	6.2902
Logarithmic	-176.8925	56.3259			3.1293	1.8905	3.3204	3.4279	5.4423
Polynomial	523.7431	-21.3020	0.3078	-0.0014	1.5474	1.0493	1.8923	1.8886	2.6912
Quadratic	62.2770	-0.9337	0.0131		2.3209	1.6166	2.8762	2.9008	4.0363
Linear	1.7283	0.8631			2.7063	1.5939	2.8513	2.9315	4.7067
Cosinusoidal	57.4779	-1.8029			7.2568	5.6781	9.6608	9.6999	12.6206
Cubic root	-111.3610	42.1472			2.9775	1.7799	3.1433	3.2417	5.1783
Self-Developed	29379.7314	298756.9626	-139464.6765	-3981.6629	1.3167	0.8718	1.5710	1.5689	2.2899

Table 5 shows the regression coefficients, and the measures of goodness of fit of the physical health measurements dataset using twelve available simple regression models and the self-formulated (proposed) model. This self-constructed model has the least values in RMSE (1.3167), MAE (0.8718), MAPE (1.5710), SMAPE (1.5689) and CV-RMSE (2.2899), where it fits best of all the other considered models. The next best performing model is the polynomial model which has the RMSE (1.5474), MAE (1.0493), MAPE (1.8923), SMAPE (1.8886) and CV-RMSE (2.6912), however it is a bit less precise than the self-developed model. To identify the best regression model the error based measures of goodness of fit of every statistic in all the models were ranked and a total rank of each model was calculated to identify the best performing model. These rankings are provided in Table 6.

Table 6. Goodness-of-fit Measures' Ranks for Physical Health Measurements Dataset

Models	Ranks						
	RMSE	MAE	MAPE	SMAPE	CV (RMSE)	Total Rank	Position
Tangential	13	12	13	12	13	63	13
Sinusoidal	11	11	11	11	11	55	11
Square root	7	6	6	6	7	32	6
Exponential	4	9	9	9	4	35	7
Power	6	3	3	3	6	21	4
Hyperbolic	10	10	10	10	10	50	10
Logarithmic	9	8	8	8	9	42	9
Polynomial	2	2	2	2	2	10	2
Quadratic	3	5	5	4	3	20	3
Linear	5	4	4	5	5	23	5
Cosinusoidal	12	13	12	13	12	62	12
Cubic root	8	7	7	7	8	37	8
Self-Developed	1	1	1	1	1	5	1

Table 6 shows the ranking of the simple regression models using five measures on goodness-of-fit based on errors (RMSE, MAE, MAPE, SMAPE and CV-RMSE) of the Physical Health Measurements data and the summative rank and position of the simple regression models. The lower ranks are more likely to achieve better results in a particular criterion and the total rank is a cumulative measure of the adequacy of the model. The regression model developed by the researcher is always first in all five goodness-of-fit measures with the total rank of 5 and the first position in the overall based on the dataset available in this study. This consistent dominance in all of RMSE, MAE, MAPE, SMAPE and CV-RMSE means that the proposed model gives the most reasonable and stable fit to the data of any of the models taken into account. It is also robust and reliable since its high performance is not pegged on one error measure.

The polynomial regression model works best of all the existing models, with a position of second in all of the five goodness-of-fit measures, making a total of 10, which is why it ends up being in the second overall position. This implies there is high predictive accuracy and consistency and this renders it the nearest rival to the self-developed model. The quadratic model ranks third at 20 totals ranking showing a good but slightly inferior performance than the polynomial model. The power model is the fourth most competitive overall with an overall rank of 21 with great performance on MAE, MAPE and SMAPE, but it is not as consistent across all the criteria as the best three models. Linear and square root model takes up the fifth and sixth positions respectively with moderate total ranks indicating that they can give acceptable but not optimal fits to their data. The exponential, cubic root and logarithmic regressions models are classified as mid-range of performance, which means that they are not very accurate when compared to the most lucrative models. Conversely, the tangential, Cosinusoidal and Sinusoidal models have the highest cumulative ranks and lowest cumulative ranks indicating relatively low performance on the error-based metrics. On the whole, the ranking outcomes provided in Table 6 have made it very clear that the self-developed regression model performs better than all other competing simple regression models on the Physical Health Measures dataset. The fact that several measures of goodness of fit are used with error and an accurate ranking methodology enhances the validity of this conclusion as it comes up with an in-depth and impartial evaluation of model performance.

However, it was ideal to examine the claim statistically by carrying out a statistical test. Hence, the Friedman technique was adopted, and the results are summarized in Table 4, and the hypotheses are stated thus:

Hypotheses Two

H_0: The performance of all the simple regression models is the same (Equal median ranks)

H_1: At least one of the simple regression models significantly performs differently

Table 7. Results of Friedman Test for Goodness-of-fit Measures' Ranks for Physical Health Measurements Dataset

Statistic	**Value**
Number of Regression Models (Treatment)	13
Number of Goodness-of-fit Measures (Blocks)	5
Friedman Chi-square (χ^2)	56.57
DF	12
p-value	0.000
Kendall's Coefficient of Concordance (V)	0.95
Decision	Reject H_0

The results of the Friedman test in Table 7 tested hypothesis two whether the difference in the performance of the simple regression models is significant statistically as measured by ranked goodness of fit measures of the Physical Health Measurements Dataset. The null hypothesis (H_0) is that the different regression models are equally ranked with respect to the median, and hence the models are not different in performance whereas the alternative hypothesis (H_1) is that at least one of the regression models is distinctly different. The Friedman test indicates Friedman chi-square = 56.57 with 12 degrees of freedom and a p-value=0.000 which is much lower than the 0.05 level of significance or significance test. This gives a good statistical indication to disregard the null hypothesis.

Therefore, the dataset does not indicate that all simple regression models yield equal results as the assumption implies. In addition, the coefficient of concordance (V = 0.95) of Kendall shows that there is a very high degree of agreement between the goodness-of-fit measures (RMSE, MAE, MAPE, SMAPE, and CV-RMSE) in ranking regression models. This high concordance ascertains the fact that the differences in model performance observed are consistent in all the measures used in the evaluation and do not depend on one measure. In general, as the Friedman test outcomes indicate, at least one of the regression models has a significant high prediction success rate compared to the others with regards to the Physical Health Measurements Dataset. This result statistically confirms the comparative analysis and is an adequate foundation to define the model with the largest performance, which, as it is indicated in the previous ranking tables, is the self-developed regression model.

4. Conclusions

A comprehensive comparative evaluation of twelve existing simple regression models versus a newly developed regression model using multiple error-based goodness-of-fit measures, such as RMSE, MAE, MAPE, SMAPE, and CV (RMSE) was conducted. This study focuses on scale-independent error behavior and predictive accuracy, which makes the evaluation more appropriate for modeling practical applications, unlike numerous past studies which relied much on coefficient of determination or information criteria measures. A hybrid simple regression model developed in this study consistently outperforms the twelve existing models in all chosen goodness-of-fit measures based on the empirical results for the two different dataset used. Its ranking superior indicates less error in predictions and more stability as compared to classical linear, polynomial and nonlinear functional forms. The Friedman test also proves that the noted differences in the performance of the regression models are statistically significant, whereas the high value of Kendall coefficient of concordance shows that there is a high level of agreement between evaluation metrics. A combination of these outcomes gives strong statistical data of the effectiveness of the proposed model.

The results reveal the significance of taking into consideration several error-related measures in evaluating the performance of regression, especially in nonlinear contexts whereby standard statistics like (R^2) can be inaccurate or misleading. Practically, the developed hybrid regression model provides a better predictive advantage within a dataset characterized by a complicated correlation, thus it may be practically applicable to such a field of application as performance evaluation, health measurement modeling and similar quantitative research. Future studies can build on this study by experimenting with the suggested model on more extensive and more heterogeneous datasets, investigating how it can withstand various noise patterns, and comparing its performance to machine learning-based regression models. Also, theoretical exploration of the asymptotic behavior and parameter stability of the model would be useful in enhancing the methodology in the model.

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Data Availability Statement

The datasets collected and analyzed during the current study are included in this study.

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Conflict of Interest

Regarding this paper publication, the authors categorically write that there is no conflict of interest. The research was carried out with complete academic integrity, and hence; no personal or financial interests have influenced the interpretations or findings being presented in this study.

Nomenclature

Z	Response (Dependent) variable
W	Explanatory (independent) variable
$\hat{Z}$	Predicted value of the response variable
ε	Random error term
R^2	Coefficient of determination
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
HQIC	Hannan-Quinn Information Criterion
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
SMAPE	Symmetric Mean Absolute Percentage Error
MAPE	Mean Absolute Percentage Error
CV (RMSE)	Coefficient of Variation of Root Mean Squared Error
V	Kendall's Coefficient of Concordance
χ^2	Friedman Chi-square

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