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HMI-Integrated Environmental Sensing for Poultry Water-Intake Forecast

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ABSTRACT

Environmental monitoring is crucial in poultry farming, yet traditional reliance on manual inspection is often labor-intensive and inefficient. This study addresses these challenges by developing a comprehensive poultry production management system. The research utilized environmental data—specifically temperature, humidity, carbon dioxide (CO₂), and ammonia (NH₃)—from a guinea fowl population at the Biaoyu Husbandry Farm in Miaoli County. The core of the system is a Human-Machine Interface (HMI) developed in MATLAB App Designer, which provides real-time data visualization, trend analysis, and an alert system for abnormal conditions. The methodology focused on robust data preprocessing, beginning with filling missing values using Shape-Preserving Cubic Interpolation (PCHIP) and correcting outliers with the Moving Median method. Subsequently, 28 daily statistical features were generated from the four primary sensor inputs, and the resulting dataset was normalized using the Z-score method. Using these features, 28 different regression models were trained to predict the daily water intake of the guinea fowl, a key indicator of poultry health. The experimental results showed that a non-linear model, the Least Squares Regression Kernel model, yielded the best performance, achieving a Root Mean Square Error (RMSE) of 0.28094, a Mean Absolute Error (MAE) of 0.21467, and an R-squared value of 0.14 on the validation set. While the model successfully captured general trends, analysis revealed larger prediction errors at extreme values, indicating opportunities for future refinement. This research provides significant benefits for poultry management by automating data collection, enabling proactive environmental control, and offering predictive insights into flock welfare, ultimately supporting data-driven decision-making to reduce manual labor and enhance production stability.

Keywords: Human-Machine Interface, Environmental Monitoring, Water-Intake Prediction, Regression Model.

INTRODUCTION

Environmental monitoring is a core technology in intelligent poultry farming, enabling real-time tracking of key variables inside poultry houses to maintain animal health and improve production stability. Traditional farm management relies heavily on manual inspections and paper records, which are inefficient and cannot meet the need for real-time data and in-depth analysis. Recent advances integrate sensor networks and IoT technologies with predictive models to monitor environmental gases, forecast drinking

and feeding behavior, and model growth. Data preprocessing, such as standardization and missing value imputation, significantly improves model accuracy and stability; for example, LSTM models have shown promising results in predicting CO₂ concentration in poultry houses. Human-Machine Interfaces (HMI) are widely used to visualize sensor data, simplify operations, and enhance on-site decision-making. Studies confirm that combining data preprocessing with regression models enhances management efficiency, and visual data interfaces allow rapid recognition of trends and anomalies, supporting smarter farming operations.

This study focuses on pearl chickens and develops a human-machine interface system featuring trend analysis and data visualization. Using shape-preserving cubic interpolation, outlier detection, and Z-score normalization, a regression model predicting daily water consumption was established. Among various tested models, the Kernel regression model demonstrated the best performance with an RMSE of 0.28094, R² of 0.14, and MAE of 0.21467 on validation data. The developed system integrates data processing, modeling, and visualization, providing a foundation for future automated monitoring and early warning systems to improve the accuracy and efficiency of intelligent poultry farming.

MATERIALS AND METHODS

Construction of a Human-Machine Interface System for Poultry Production Management

The poultry production management system developed in this study is built on the MATLAB App Designer platform, designed with a Human–Machine Interface (HMI) featuring real-time monitoring and data visualization capabilities. The system was initially developed to assist farm managers in obtaining and interpreting changes in environmental parameters on-site in real time. Through a clear and intuitive user interface combined with dynamic visual aids, it aims to reduce the workload of daily inspections while enhancing the ability to quickly respond to and handle abnormal conditions. This, in turn, promotes the digital transformation and intelligent management of traditional farming operations.

This system integrates four key sensor variables critical to the rearing environment: temperature (TEMP), relative humidity (RH), carbon dioxide (CO₂) concentration, and ammonia (NH₃) concentration. These environmental parameters serve as vital references for climate control within poultry houses and maintaining poultry health. They are also highly correlated with production indicators such as water intake, feed consumption, growth rate, and disease risk. Therefore, their real-time monitoring and trend analysis have a substantial impact on breeding management.

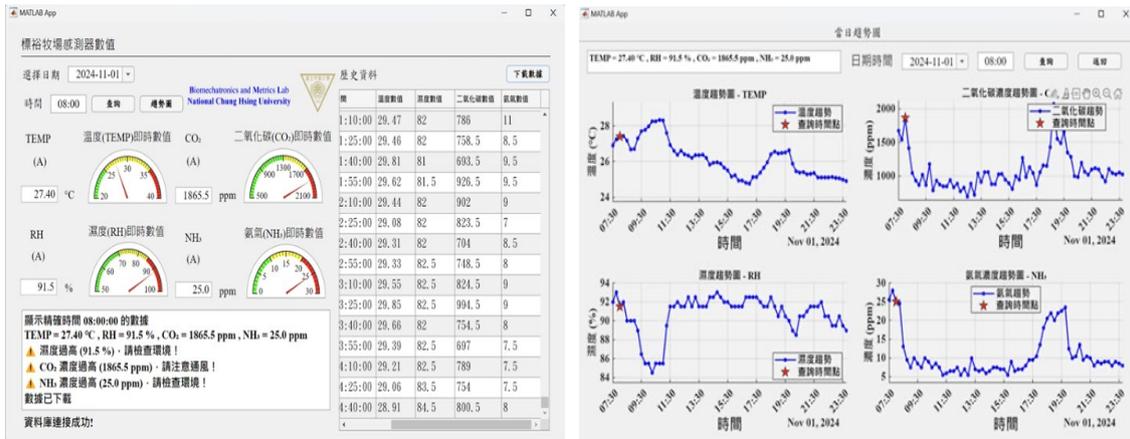


Fig.1 (A) Sensor data displayed on the Human–Machine Interface; (B) Daily trend chart

In Interface A of Figure 1, users can select a specific date and time using the date-time picker located at the upper left corner. After selection, the system automatically retrieves real-time data from the database for that time point and immediately displays it on the central dashboard of the interface, including values for temperature, relative humidity, carbon dioxide concentration, and ammonia concentration. The right-side area presents all the original historical data stored in the database for that selected date, allowing users to conveniently review the data. Users can also download all historical raw data via the download data function located at the upper right corner. Furthermore, when any sensor parameter exceeds the safety threshold set on the dashboard, the system automatically activates alert indicators, clearly showing warning icons and text prompts in the lower section of the interface to promptly notify managers of abnormal conditions and items requiring attention.

Figure 1 B displays the system's trend chart module, which presents daily variation trends for temperature, relative humidity, carbon dioxide, and ammonia through four separate line charts. The red asterisks on the charts mark the data points corresponding to the current queried time, making it easier to precisely grasp parameter information at specific time points. This assists in analyzing potential correlations between environmental fluctuations and poultry health and production efficiency.

The development of this interface has also taken future integration needs into consideration. Therefore, the data structure is stored in a standardized format and retains data export functionality, enabling direct application for regression model training and predictive analysis in the future. It can also be integrated with on-site decision-making modules or IoT monitoring platforms.

Data preprocessing and analysis

The data downloaded from the Human–Machine Interface, as shown in Figure 2, is in CSV file format. It must first be converted into a table format using MATLAB and loaded into the Workspace before using MATLAB's Data Cleaner tool for data processing. The first step is to perform missing value interpolation. In this study, shape-preserving cubic interpolation (PCHIP) is used for imputation to ensure that the trend of the interpolated data curve remains consistent with the original data.

Date_Stamp	Time_Stamp	TEMP_Avg	RH_Avg	CO2_Avg	NH3_Avg
2024/7/5	14:45:00	33.83	75	575.5	0
2024/7/5	15:00:00	33.75	76	571	0
2024/7/5	15:15:00	33.79	76	585.5	0
2024/7/5	15:30:00	33.9	75	575.5	0
2024/7/5	15:45:00	33.83	75	577	0
2024/7/5	16:00:00	33.71	75	579.5	0.5
2024/7/5	16:15:00	33.6	75.5	571.5	0
2024/7/5	16:30:00	33.54	75.5	566.5	0
2024/7/5	16:45:00	33.52	76	576	0
2024/7/5	17:00:00	33.34	75.5	572.5	0
2024/7/5	17:15:00	32.97	76	567	0
2024/7/5	17:30:00	32.55	77.5	565.5	0
2024/7/5	17:45:00	32.27	79.5	573	0
2024/7/5	18:00:00	31.89	80	566.5	0
2024/7/5	18:15:00	31.69	80.5	584	0
2024/7/5	18:30:00	31.55	81.5	579.5	0
2024/7/5	18:45:00	31.36	81.5	578.5	0
2024/7/5	19:00:00	31.16	81.5	594	0
2024/7/5	19:15:00	31.02	82.5	598	0
2024/7/5	19:30:00	30.8	83.5	602	0
2024/7/5	19:45:00	30.7	82.5	596	0
2024/7/5	20:00:00	30.62	83	592.5	0
2024/7/5	20:15:00	30.49	83.5	597	0
2024/7/5	20:30:00	30.4	83.5	589	0
2024/7/5	20:45:00	30.24	84	599.5	0.5
2024/7/5	21:00:00	30.14	84.5	597.5	0

Fig.2 Original data

Next, outlier handling is performed to prevent abnormal data from misleading subsequent analysis and prediction results. Afterward, for the four factors—temperature (TEMP), relative humidity (RH), carbon dioxide (CO₂), and ammonia (NH₃)—daily statistics are calculated, including the mean, maximum, minimum, standard deviation (std), median, range, and interquartile range (IQR), producing a total of 28 feature items.

The statistical feature aggregation process is as follows: first, data are grouped by date; then, the above daily statistical features are calculated using built-in MATLAB functions to create a daily summary table.

Once the data summarization is completed, Z-score normalization is applied for data standardization.

Date	mean_TEMP	max_TEMP	min_TEMP	std_TEMP	median_TEMP	range_TEMP	IQR_TEMP	mean_RH	max_RH	min_RH	std_RH	median_RH	range_RH	IQR_RH	mean_CO2	max_CO2	min_CO2	std_CO2	median_CO2	range_CO2	IQR_CO2	mean_NH3	max_NH3	min_NH3	std_NH3	median_NH3	range_NH3	IQR_NH3
5-Jul-24	1.1557	0.58545	-1.3074	0.82001	0.62829	0.96172	-1.40781	-0.88017	1.40005	0.0693	-0.83222	-0.50932	-0.12249	-0.13401	-1.19857	-0.09562	1.176	-0.45843	-1.2434	-0.79468	-0.5276	-0.75412	-1.32918	0.00003	0.18939	0.49328	-1.1508	-0.82753
6-Jul-24	0.66535	0.07323	-1.00259	-0.81664	0.70888	-0.18822	-1.06534	-0.83656	0.68001	0.27101	-0.44156	-0.50932	0.47211	-0.36137	-0.88835	-0.86965	0.66642	-0.00629	-0.92599	-0.79468	0.61629	-0.44491	-1.03478	-0.85761	0.152345	-0.51205	-0.87663	-0.82753
7-Jul-24	0.8976	-0.92557	-1.16458	-0.78526	0.99006	-1.11642	-1.20992	-0.76937	0.43067	-0.7953	-0.72263	-0.50932	1.62163	0.64597	-0.91267	-0.72284	0.95321	-0.40191	-1.01229	-0.79468	1.28979	0.1735	-1.12388	-0.77838	1.998317	1.00501	-0.71669	-0.82425
8-Jul-24	0.25204	-0.75764	-1.20388	-0.82001	0.40173	-0.96172	-1.19425	-0.88017	0.07201	-1.15273	-0.95151	-0.50932	0.8392	0.57921	-0.8543	-0.90562	0.05491	-0.40191	-1.14111	-0.79468	0.64889	0.68884	-1.05117	-0.90003	0.571976	0.40528	-0.47145	-0.82753
9-Jul-24	0.52292	-0.34152	-1.3794	-0.82001	0.67945	-1.11642	-1.18641	-0.88017	-0.27401	-0.39194	-0.81991	-0.50932	2.0141	-0.10314	-1.06203	-0.90562	0.71392	-1.09013	-1.28628	-0.79468	1.5929	0.07043	-1.05651	-0.90003	2.531905	-0.65339	-1.07178	-0.82753
10-Jul-24	0.56768	-0.44245	-1.24486	-0.81904	0.73061	-0.49762	-1.19425	-0.85927	0.46319	-0.43788	-0.88811	-0.50932	0.69556	-0.05925	-1.01751	-0.89171	0.44599	-0.45843	-1.14315	-0.79468	0.77113	0.1735	-1.07339	-0.88439	0.259964	-0.65339	-0.95786	-0.82753
11-Jul-24	0.71108	-0.49412	-1.31822	-0.65948	0.68676	-0.34202	-1.19229	-0.76937	0.62581	-0.25914	-0.84201	-0.46625	0.58964	0.04454	-0.88539	-0.74553	0.86077	-1.02361	-1.27606	-0.58102	0.48823	0.07043	-1.05651	-0.79433	0.828272	0.27423	-0.98833	-0.67634
12-Jul-24	0.80987	-0.94792	-1.47486	-0.63699	0.47846	-1.88993	-1.37646	-0.76937	0.7288	-0.08042	-1.0883	-0.50932	0.28176	-0.88481	-1.21913	-0.7634	1.02005	-1.02361	-1.37012	-0.57357	-0.02369	-1.16639	-1.2195	-0.77838	0.419684	-0.51205	-1.21046	-0.82753
13-Jul-24	0.89655	-0.8735	-1.36126	-0.81327	0.61002	-1.11642	-1.41369	-0.80443	1.09946	-0.76994	-1.008	-0.50932	0.26966	-0.07261	-1.16401	-0.83842	1.04801	-1.13665	-1.20245	-0.79468	0.19208	0.07043	-1.28469	-0.81972	0.443828	-0.11891	-1.02041	-0.82753
14-Jul-24	0.94188	-1.79365	-1.27332	-0.82001	1.2349	-1.11642	-1.03162	-0.88017	0.43067	-2.13569	-1.28848	-0.50932	1.66005	1.85095	-0.73373	-0.90562	0.78966	-1.30621	-1.19427	-0.79468	1.74109	1.71953	-0.78853	-0.90003	1.233144	1.78126	-0.68876	-0.82753
15-Jul-24	0.99955	-0.63105	-1.05216	-0.82001	1.10334	-0.65232	-0.98264	-0.88017	0.72338	-1.06338	-0.85732	-0.50932	1.24773	1.04311	-0.66114	-0.90562	1.02005	-0.23236	-0.96955	-0.79468	1.34887	0.79191	-0.84789	-0.90003	1.307433	0.94948	-0.47298	-0.82753
16-Jul-24	1.14859	-0.80156	-1.1424	-0.82001	0.94621	-0.49762	-1.00236	-0.88017	0.92394	-0.7953	-0.85732	-0.50932	0.82613	1.01532	-0.87228	-0.90562	1.26844	-0.62799	-1.02251	-0.79468	0.596	0.58577	-0.96959	-0.90003	0.820843	1.25708	-0.47571	-0.82753
17-Jul-24	1.05734	-1.08384	-1.20124	-0.82001	0.86582	-1.11642	-1.09824	-0.88017	0.81553	-0.61658	-0.81882	-0.50932	0.92117	0.34379	-0.90503	-0.90562	1.1286	-0.91058	-1.19836	-0.79468	0.58253	-0.02364	-0.98967	-0.90003	0.960134	0.66737	-0.47298	-0.82753
18-Jul-24	1.1483	-1.4503	-1.28508	-0.82001	1.18008	-1.11642	-1.24911	-0.88017	0.53908	-1.15273	-0.98051	-0.50932	1.48007	1.11651	-0.93398	-0.90562	1.29214	-0.68485	-1.14724	-0.79468	1.50533	0.58577	-1.10867	-0.90003	1.333434	1.66737	-0.47571	-0.82753
19-Jul-24	1.16034	-0.26443	-1.08838	-0.82001	0.8512	-1.18822	-1.10412	-0.88017	0.99983	0.18765	-0.61094	-0.50932	0.49276	0.19177	-0.88627	-0.90562	1.27081	-0.23236	-1.08181	-0.79468	0.32657	-0.34184	-1.05217	-0.90003	0.702695	0.61084	-0.70653	-0.82753
20-Jul-24	1.14408	-0.57004	-0.98346	-0.82001	0.96448	-0.18822	-0.98264	-0.88017	0.93478	-0.88466	-0.77263	-0.50932	0.74902	1.12607	-0.66404	-0.90562	1.20208	-0.17584	-0.84053	-0.79468	0.61621	0.89498	-0.87118	-0.90003	0.553404	1.19155	-0.37397	-0.82753
21-Jul-24	1.13111	-0.60392	-1.11933	-0.82001	0.8987	-0.18822	-1.04142	-0.88017	1.39553	-0.61658	-1.0113	-0.50932	0.02628	0.67503	-0.75098	-0.90562	1.09395	-0.62799	-1.08817	-0.79468	0.07757	0.58577	-0.86963	-0.90003	0.011097	0.73289	-0.76492	-0.82753
22-Jul-24	1.15301	-0.58713	-1.19215	-0.82001	1.04122	-0.34202	-1.05114	-0.88017	0.74506	-0.3485	-0.97281	-0.50932	1.00726	0.54982	-0.81494	-0.90562	1.25659	-0.23236	-1.09222	-0.79468	0.93942	0.1735	-0.8957	-0.90003	1.080853	0.66737	-0.75477	-0.82753
23-Jul-24	1.23729	-1.80763	-1.31479	-0.82001	1.54916	0.12118	-0.92586	-0.88017	0.90226	-2.3144	-1.82743	-0.50932	1.43431	3.01262	-0.08501	-0.90562	1.14993	-1.87139	-1.42533	-0.79468	1.73435	2.75021	-0.58089	-0.90003	0.932226	3.15725	0.89172	-0.82753
24-Jul-24	-0.07285	1.91992	-1.21638	-0.82001	-0.77129	1.51349	-1.12175	-0.88017	0.36674	1.90676	-1.21918	-0.50932	-2.0451	-1.72995	-0.8984	-0.90562	0.05728	1.57623	-1.10839	-0.79468	-2.74747	-0.90626	-0.90003	-0.90003	-1.68182	-1.28633	-1.09898	-0.82753
25-Jul-24	0.66767	1.91992	-0.78783	-0.76992	1.28096	1.51349	-1.08257	-0.76992	-0.25512	2.0744	-0.16438	-0.50932	-1.48038	-1.2823	-1.08818	-0.82618	-0.4215	1.05153	-0.95972	-0.58985	-1.88276	-1.7848	-1.5144	-0.77838	-1.05752	-1.28633	-1.10663	-0.82753
26-Jul-24	0.51599	0.82105	-1.18855	-0.66743	-0.0102	0.99468	-1.27964	-0.76937	-0.1385	0.90253	-0.68789	-0.50932	-1.48679	-0.88786	-1.1623	-0.64071	-0.30908	0.5599	-1.07158	-0.57357	-0.93975	-0.44491	-1.21515	-0.77838	-1.68268	-1.08623	-1.15588	-0.82753
27-Jul-24	0.26605	0.62456	-0.79446	-0.82001	0.32133	1.35979	-0.76124	-0.88017	0.49571	-0.08042	-0.54059	-0.50932	-0.08189	0.53991	-0.5318	-0.90562	0.12828	0.33282	-0.82017	-0.79468	0.02369	0.99885	-0.68926	-0.90003	-0.06691	0.07766	-0.46161	-0.82753
28-Jul-24	0.70075	-0.10716	-0.77464	-0.82001	0.91989	1.35979	-0.79259	-0.88017	0.54618	-1.33145	-0.82653	-0.50932	1.16028	2.72386	-0.28188	-0.90562	0.64546	-0.00629	-0.82212	-0.79468	0.89668	2.44101	-0.64579	-0.90003	1.140284	2.82363	0.00176	-0.82753
29-Jul-24	0.27455	1.00176	-0.76787	-0.82001	0.21536	0.73998	-0.83096	-0.88017	0.60986	0.63445	-0.13187	-0.50932	-0.16878	-0.1699	-0.68314	-0.90562	0.22082	1.12408	-0.27193	-0.79468	0.46151	-0.23878	-0.87614	-0.90003	-0.17402	-0.11891	-0.42451	-0.82753
30-Jul-24	0.42327	0.15435	-0.96655	-0.75753	0.50199	0.43958	-0.97872	-0.76937	0.30957	-0.08042	-0.57704	-0.50932	1.04943	0.95825	-0.76512	-0.67354	0.31326	0.27631	-0.94276	-0.79468	0.54885	0.37964	-0.9633	-0.77838	1.348202	1.00501	-0.61768	-0.5566
31-Jul-24	0.43388	0.37266	-1.00246	-0.81689	0.32133	1.04919	-1.13351	-0.81557	0.07201	0.36674	-0.57704	-0.50932	0.88566	0.65956	-0.80700	-0.81985	0.52657	0.10675	-0.90596	-0.79468	0.5017	0.27857	-0.10963	-0.82386	1.349631	0.89191	-1.12796	-0.82001
1-Aug-24	0.62304	0.10268	-1.17862	-0.82001	0.47846	-0.34202	-1.28242	-0.88017	0.65833	0.45573	-0.62634	-0.50932	0.24121	-0.2026	-1.17303	-0.90562	0.63323	0.44586	-1.01637	-0.79468	0.06388	-0.75412	-1.24557	-0.90003	0.419684	-0.11891	-1.12796	-0.82753
2-Aug-24	0.97908	-1.03141	-1.29176	-0.82001	0.82562	-0.49762	-1.30005	-0.88017	0.75048	-0.97402	-1.0421	-0.50932	0.97909															

Training of regression models

This study used the Regression Learner tool provided by MATLAB to perform regression model training. The dataset consisted of 120 records of daily sensor statistical feature data, including 28 feature variables such as daily mean, maximum, minimum, standard deviation, median, range, and interquartile range, used to predict the daily water intake of chickens.

The training data employed 5-fold cross-validation to validate the models, effectively reducing the risk of overfitting and improving the models' generalization ability. Additionally, 10% of the data was set aside as an independent test set for testing and evaluation after model training, to verify the model's predictive performance and accuracy on real-world data.

RESULTS & DISCUSSION

This study used the MATLAB Regression Learner tool to train and validate 28 different types of regression models for predicting the daily water intake of chickens. After comparing the models based on their Root Mean Square Error (RMSE) during validation, it was found that the Kernel model (Least Squares Regression Kernel) performed the best, achieving an RMSE of 0.28094 and an R-squared value of 0.14. This indicates that the model demonstrates relatively better predictive accuracy and stability.

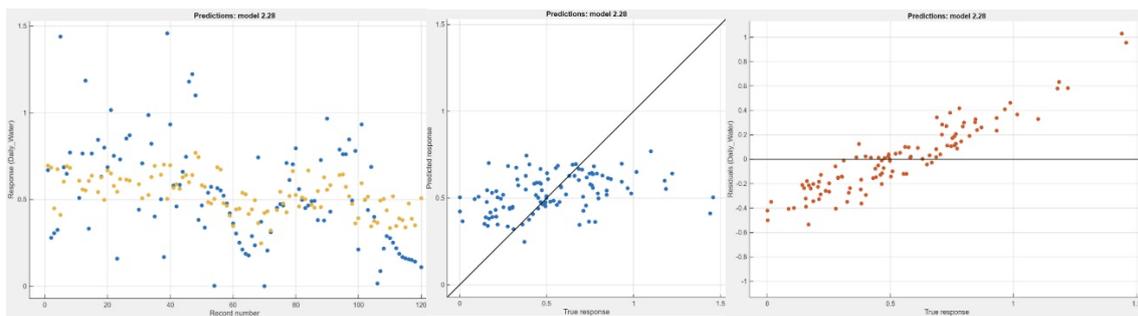


Fig.4 (A) Scatter Plot of Kernel Model Predicted Values versus Actual Values; (B) Plot Comparing Kernel Model Predictions and Actual Observations; (C) Residuals Plot of the Kernel Regression Model

Further analyzing the prediction results of the Kernel model, the distribution of actual versus predicted values shows that while the overall trend is reasonably captured, there remain relatively large errors at certain extreme values, especially in the regions of higher or lower actual daily water intake. Observations from the residuals plot reveal a certain linear trend between residuals and true values, suggesting that the model may still miss some nonlinear patterns or other latent interactions. Additionally, some observations exhibit considerable prediction errors, possibly due to data heterogeneity or the complexity of environmental factors, which limits the model's performance in capturing extreme cases.

Among other models, the Medium Gaussian Support Vector Machine (SVM) and Exponential Gaussian Process Regression also performed well in terms of RMSE, with values of 0.27976 and 0.28924 respectively, indicating these models can effectively capture the relationship between feature variables and the target variable. However, compared to the Kernel model, their R-squared values are lower, implying weaker explanatory power.

On the other hand, linear regression type models (such as the Interactions Linear model with RMSE 2.3388) and neural network type models (such as the Narrow Neural Network

model with RMSE 0.59151) performed significantly worse. This is likely because the dataset contains strong nonlinear relationships or complex feature interactions that simpler linear or structurally less complex models cannot effectively capture.

CONCLUSIONS

This study employed the MATLAB Regression Learner tool to compare and analyze 28 regression models for predicting the daily water intake of chickens. The results showed that the Kernel model (Least Squares Regression Kernel) exhibited the best predictive performance (RMSE = 0.28094, $R^2 = 0.14$), effectively capturing the nonlinear relationship between sensor features and chicken water intake. Additionally, the Medium Gaussian Support Vector Machine (SVM) and Exponential Gaussian Process Regression models also demonstrated good predictive capabilities.

However, the Kernel model showed larger prediction errors in extreme values—specifically in regions with particularly high or low water intake—reflecting possible data heterogeneity or other latent factors not incorporated into the model. Based on these findings, future work is recommended to conduct more in-depth feature engineering or to include additional relevant variables, such as environmental management practices and physiological indicators of the chickens, to further improve the model's accuracy and practical applicability.

In summary, this study validates that nonlinear regression models are more suitable for poultry house production management systems. Going forward, such models should be prioritized as effective tools to enhance the precision and efficiency of agricultural management.

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