adjustment of the degree parameter, which helped reduce overfitting and adjust the complexity to the data. In contrast, the Linear kernel remained stable at 0.5600, as its linearity made hyperparameter tuning less impactful. These results confirm that hyperparameter tuning has a greater impact on complex kernels such as RBF and Polynomial than the simpler Linear kernel.

C. Model Validation

Model validation was performed using internal and external approaches. In internal validation, we calculated R^2_{Train} and Q^2_{LOO} to measure the performance of the model on training data. While in external validation, R^2_{Test} is used to measure the generalization of the model on data that has never been seen before. The model is considered feasible if the R^2 and Q^2 score exceed the predefined thresholds of 0.6 and 0.5, respectively. In addition, several other validation metrics are also considered to ensure the quality of the model.

TABLE VII.
CALCULATED STATISTICAL PARAMETERS FOR SVM KERNELS (TRAIN SET)

Parameter	RBF	Linear	Poly	Threshold
R^2	0.8728	0.7762	0.7803	>0.6
Q^2	0.6470	0.6313	0.6108	>0.5
k'	1.0213	1.0260	1.0262	$0.85 \leq k' \leq 1.15$
$\frac{(r^2 - r'^2_0)}{r^2}$	0.0053	0.0019	0.0054	<0.1
$\lvert r^2_0 - r'^2 \rvert$	0.0386	0.0798	0.0961	<0.3
r^2_m	0.8137	0.7461	0.7297	>0.5
Δr^2_m	0.1223	0.1912	0.1966	<0.2

TABLE VIII.
CALCULATED STATISTICAL PARAMETERS FOR SVM KERNELS (TEST SET)

Parameter	RBF	Linear	Poly	Threshold
R^2	0.5620	0.4869	0.4873	>0.6
Q^2	0.6470	0.6314	0.6108	>0.5
k'	0.9918	0.7282	0.7955	$0.85 \leq k' \leq 1.15$
$\frac{(r^2 - r'^2_0)}{r^2}$	0.0106	0.1497	0.2874	<0.1
$\lvert r^2_0 - r'^2 \rvert$	0.1561	0.0002	0.1117	<0.3
r^2_m	0.5187	0.3555	0.3049	>0.5
Δr^2_m	0.1829	0.0001	0.1003	<0.2

In In Table VII and Table VIII, the RBF kernel achieved the best performance with R^2_{Train} of 0.8728, as well as Q^2_{LOO} of 0.6470, reflecting reliable prediction in leave-one-out (LOO) cross validation, and R^2_{Test} of 0.5620. While these results demonstrate the model's ability to capture patterns in the training data, the significant decrease in R^2_{Test} indicates potential overfitting. This discrepancy may arise due to the limited size of the dataset, which may limit the model's ability to generalize to unseen data.

IV. CONCLUSION

This study develops a prediction model using Camel Algorithm (CA) for feature selection and Support Vector Machine (SVM) equipped with hyperparameter tuning to predict Angiotensin Converting Enzyme (ACE) Inhibitors as antihypertensive drugs. Feature selection with CA improves model efficiency by filtering out relevant features, while hyperparameter tuning ensures optimal parameters, such as gamma and C in the RBF kernel, resulting in the best performance with R^2_{Train} of 0.8728 and R^2_{Test} of 0.5620. This study demonstrates the effectiveness of Camel Algorithm in optimizing feature selection and improving model efficiency. However, the validation results highlighted the potential for overfitting, which can be addressed by applying techniques such as hyperparameter regularization and combining cross-validation with larger datasets. These approaches will not only reduce the risk of overfitting but also improve the model's ability to generalize to unseen data. In addition, exploration of additional validation metrics, such as RMSE or MAE, can provide a more comprehensive evaluation of model performance. Further development is needed, including the use of larger data sets and the exploration of other algorithms, so that this methodology can pave the way for further advances in drug discovery and antihypertensive therapy.

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