COMPUTER VISION TARGET DETECTION – DATA ANALYSIS

Introduction:

In the realm of machine vision and machine learning systems, the ability to accurately detect targets in a given field of view is crucial. These systems rely on sensors such as SONAR, RF, IR, or LIDAR to collect data from the region of interest. The collected data is then analyzed to determine whether a target is present or absent. However, due to various uncertainties such as noise, operator variability, and measurement conditions, there is often an overlap in the data values between the "target present" and "target absent" scenarios. This overlap complicates the decision-making process, making it essential to employ robust statistical methods to enhance the system's performance.

This project focuses on the statistical analysis of machine vision systems by examining the performance of target detection through Receiver Operating Characteristic (ROC) analysis, hypothesis testing, and signal processing techniques. The primary goal is to improve the system's ability to distinguish between "target absent" and "target present" cases by analyzing the data's statistical properties and applying signal processing methods. The project is divided into three main parts: ROC analysis, hypothesis testing, and performance enhancement through signal processing. Each part builds on the previous one, culminating in a comprehensive evaluation of the system's performance.

Target Absent (sorted)							Target Present(sorted)					
0.2288	0.9738	1.5155	1.8134	2.4642	3.0016	3.7414	0.8502	3.597	5.038	6.2148	7.9063	9.0267
0.2875	1.0357	1.5392	1.8824	2.475	3.0561	4.1963	1.3036	3.6666	5.0466	6.2783	8.0351	9.1138
0.4245	1.0849	1.5783	1.9233	2.4948	3.0795	4.3419	1.9509	3.6946	5.0566	6.4274	8.1055	9.1986
0.5614	1.105	1.6009	1.9744	2.5165	3.1672	4.4062	2.2823	3.9009	5.316	6.4378	8.1411	9.5672
0.5913	1.1065	1.6243	2.1383	2.5464	3.1888	4.517	2.3655	3.9923	5.4776	6.7311	8.1493	9.7048
0.7033	1.1195	1.7005	2.157	2.6294	3.1943	4.5275	2.7687	4.1211	5.7676	7.2483	8.1898	9.8689
0.7034	1.339	1.706	2.1672	2.7189	3.2471	4.6435	3.0907	4.1744	5.7751	7.2815	8.2283	10.6644
0.7436	1.3416	1.7289	2.2572	2.8169	3.4611	4.8878	3.152	4.4304	6.0034	7.2903	8.4848	12.2697
0.805	1.3448	1.7524	2.3297	2.8212	3.5686	5.2738	3.3261	4.505	6.0153	7.4981	8.6014	12.4364
0.8718	1.398	1.759	2.4492	2.9868	3.7295	5.9835	3.3267	4.5079	6.0467	7.5408	8.6172	12.4508

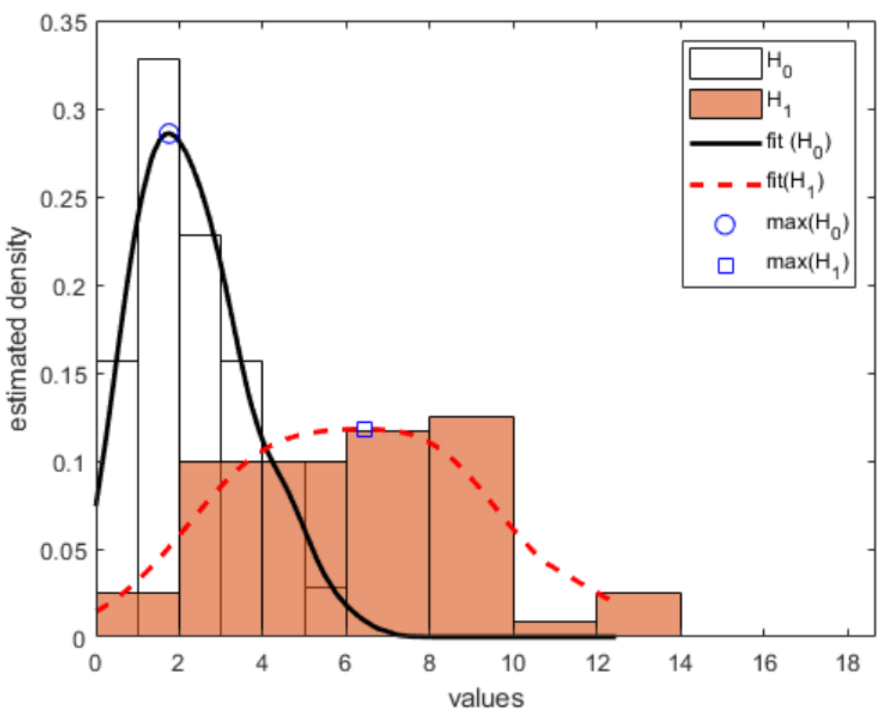
mean $\mu_1 = 2.301$, var $\sigma_1^2 = 1.702$ mean $\mu_2 = 6.271$, var $\sigma_2^2 = 7.582$

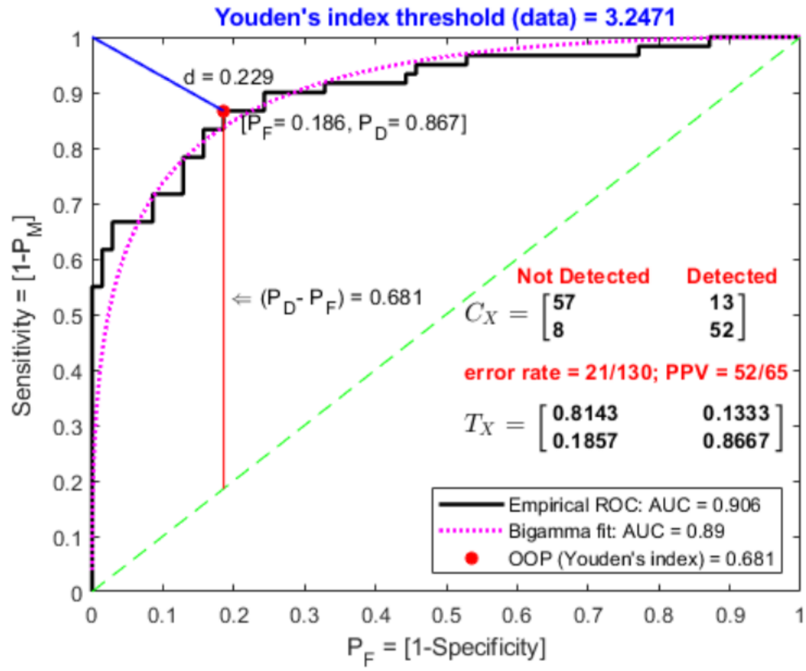
$$\text{Performance Index PI} = \frac{|\mu_1 - \mu_2|}{\sqrt{\sigma_1^2 + \sigma_2^2}} = \mathbf{1.303}$$

Part 1:

ROC analysis evaluates target detection performance by estimating empirical densities for "target absent" and "target present" data. The intersection of these densities helps identify a threshold, but the optimal threshold is determined using Youden's index, maximizing the difference between true positive rate (TPR) and false positive rate (FPR). The ROC curve is then plotted, showing TPR vs. FPR, and the Area Under the Curve (AUC) quantifies system performance.

At the optimal threshold, a confusion matrix is created, detailing true/false positives and negatives. Key metrics like error rate, positive predictive value (PPV), and detection probabilities are derived. This analysis provides a clear evaluation of the system's ability to distinguish targets, laying the groundwork for further optimization.





Confusion and Transition Matrices (mid-point and intersection thresholds)

Threshold (v_T) = 4.1211 (midpoint)

$$C_X = \begin{bmatrix} N_0 - N_F & N_F \\ N_1 - N_C & N_C \end{bmatrix} = \begin{array}{cc} \text{Not Detected} & \text{Detected} \\ \begin{bmatrix} \mathbf{61} \\ \mathbf{16} \end{bmatrix}\!\!\!\! & \begin{bmatrix} \mathbf{9} \\ \mathbf{44} \end{bmatrix} \end{array} \begin{array}{l} \text{(Target Absent)} \\ \text{(Target Present)} \end{array}$$

error rate = 25/130, PPV = 44/53

$$T_X = \begin{bmatrix} 1 - P_F & P_M \\ P_F & 1 - P_M \end{bmatrix} = \begin{bmatrix} \mathbf{0.8714} & \mathbf{0.2667} \\ \mathbf{0.1286} & \mathbf{0.7333} \end{bmatrix} \begin{array}{l} \rightarrow \text{dist. to } [0,1] = 0.296 \\ \rightarrow [P_D\text{-}P_F] = 0.6048 \end{array}$$

Prob(TargetNotDetected) = 77/130, Prob(TargetDetected) = 53/130

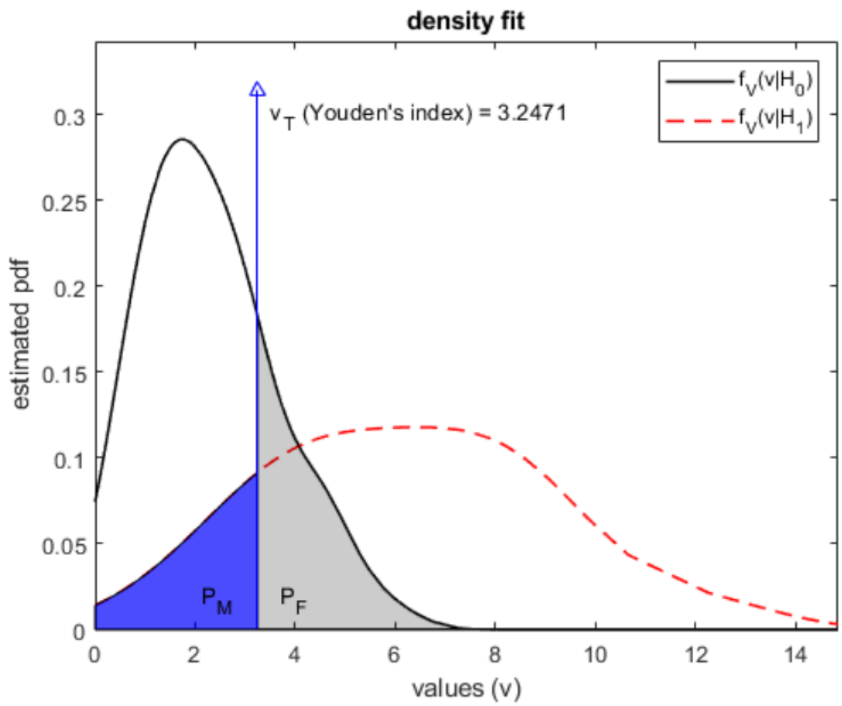
Threshold (v_T) = 4.1211 (intersection)

$$C_X = \begin{bmatrix} N_0 - N_F & N_F \\ N_1 - N_C & N_C \end{bmatrix} = \begin{array}{cc} \text{Not Detected} & \text{Detected} \\ \begin{bmatrix} \mathbf{61} \\ \mathbf{16} \end{bmatrix}\!\!\!\! & \begin{bmatrix} \mathbf{9} \\ \mathbf{44} \end{bmatrix} \end{array} \begin{array}{l} \text{(Target Absent)} \\ \text{(Target Present)} \end{array}$$

error rate = 25/130, PPV = 44/53

$$T_X = \begin{bmatrix} 1 - P_F & P_M \\ P_F & 1 - P_M \end{bmatrix} = \begin{bmatrix} \mathbf{0.8714} & \mathbf{0.2667} \\ \mathbf{0.1286} & \mathbf{0.7333} \end{bmatrix} \begin{array}{l} \rightarrow \text{dist. to } [0,1] = 0.296 \\ \rightarrow [P_D\text{-}P_F] = 0.6048 \end{array}$$

Prob(TargetNotDetected) = 77/130, Prob(TargetDetected) = 53/130



Part 2:

In Part 2, the focus is on hypothesis testing to model the statistical properties of the data and further evaluate the system's performance. The goal is to identify the best-fitting probability distributions for the "target absent" and "target present" datasets using χ^2 goodness-of-fit tests. Several distributions, including Weibull, Nakagami, Rician, Gamma, Rayleigh, and Lognormal, are tested, and the one with the highest p-value (exceeding 0.05) is selected as the best fit for each scenario. Once the best-fitting distributions are identified, parametric bootstrapping is performed by generating synthetic datasets based on these distributions. The Area Under the ROC Curve (AUC) is calculated for each synthetic dataset, and this process is repeated 5,000 times to obtain the mean and standard deviation of the AUC. Additionally, non-parametric bootstrapping is conducted on the original data to compare results and ensure robustness.

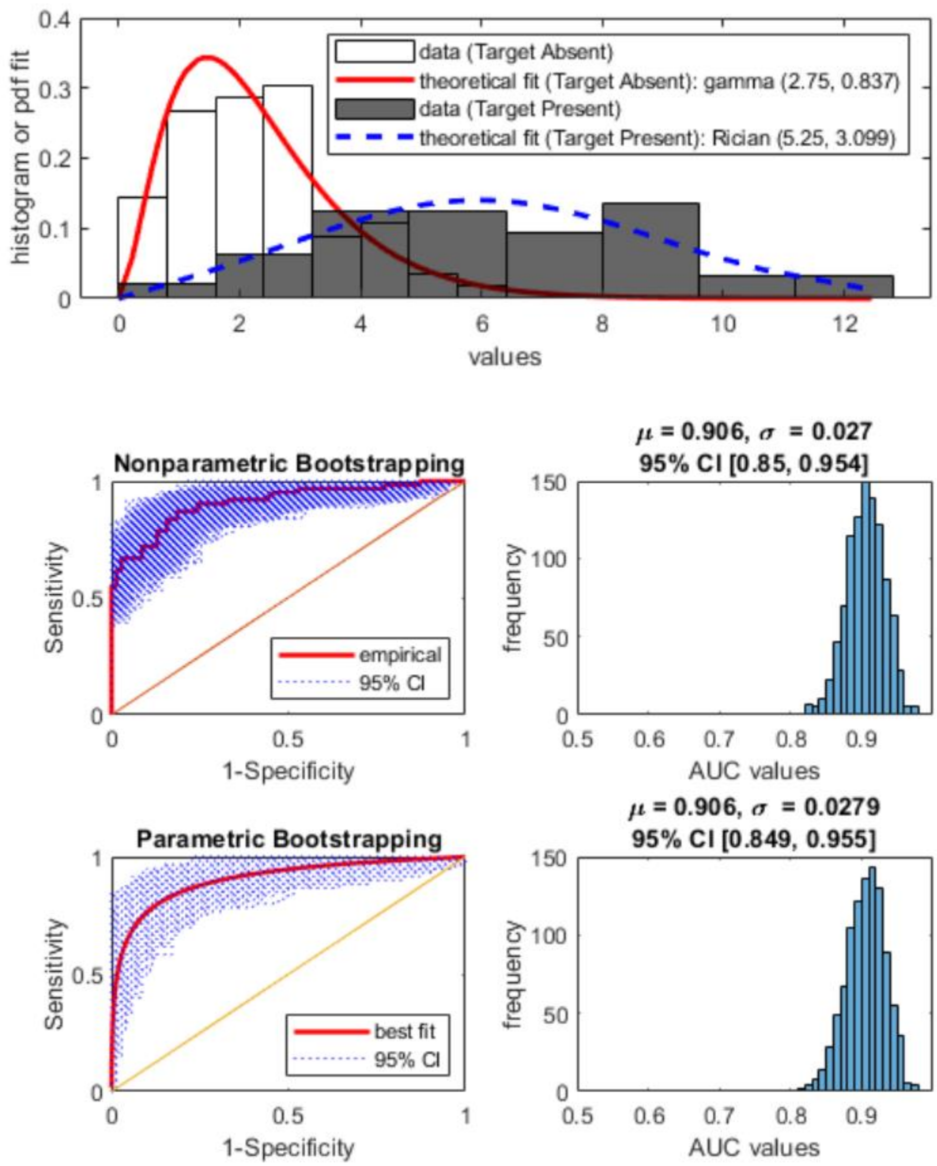
The results are visualized through ROC curves, where the empirical ROC from the original data is plotted alongside the theoretical ROC based on the best-fitting distributions and the bigamma fit from Part 1. The 95% Confidence Interval (CI) of the AUC is also displayed on the ROC plot, providing a range of expected performance. Key metrics, such as the mean and standard deviation of the AUC, are calculated using both bootstrapping methods and the Hanley and McNeil formula. This analysis confirms the system's ability to distinguish between "target present" and "target absent" scenarios with high reliability, while also validating the chosen statistical models. The findings set the stage for further performance enhancement in Part 3.

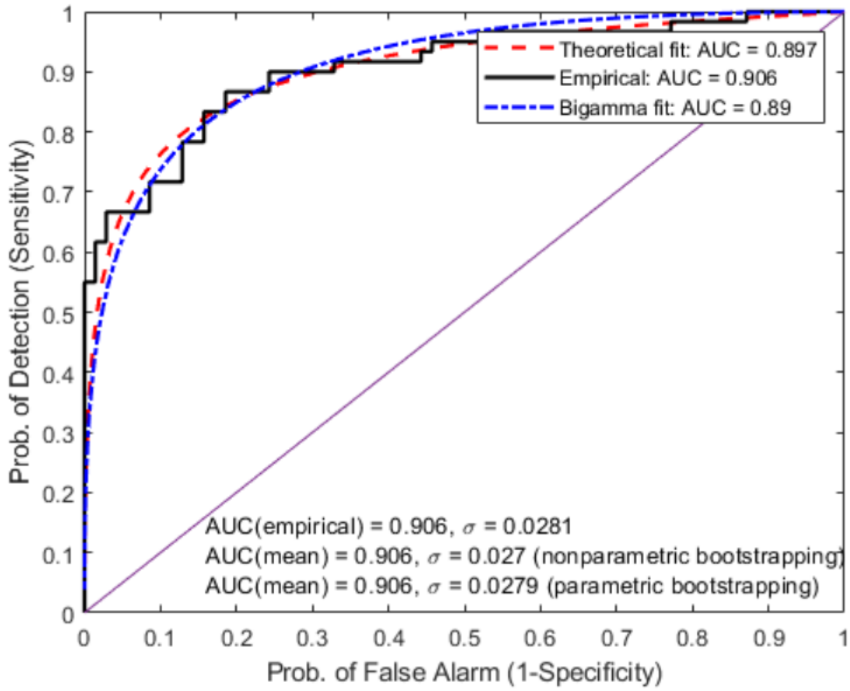
summary of χ^2 tests

	DoF	χ^2_{stat}	p-val	DoF	χ^2_{stat}	p-val
Weibull	3	2.902	**0.407**	4	2.913	**0.5725**
Nakagami	3	3.16	**0.3673**	4	3.55	**0.4701**
Gamma	4	3.918	**0.4173**	4	6.136	**0.1893**
Rician	3	4.598	**0.2037**	4	2.668	**0.6149**
Rayleigh	4	4.603	**0.3305**	5	6.138	**0.293**
lognormal	4	7.19	**0.1263**	4	11.25	**0.0239**

Target Absent
gamma hypothesis not rejected

Target Present
Rician hypothesis not rejected



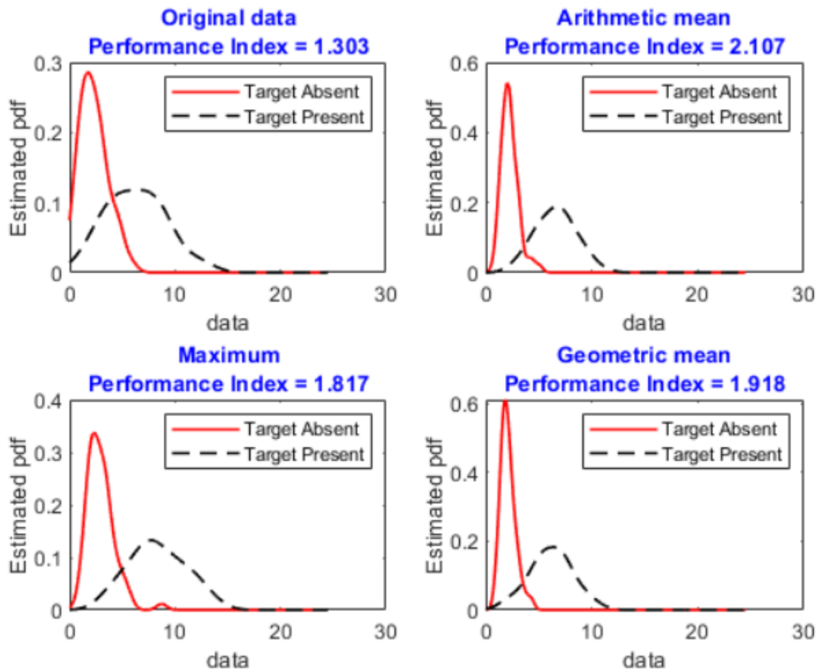


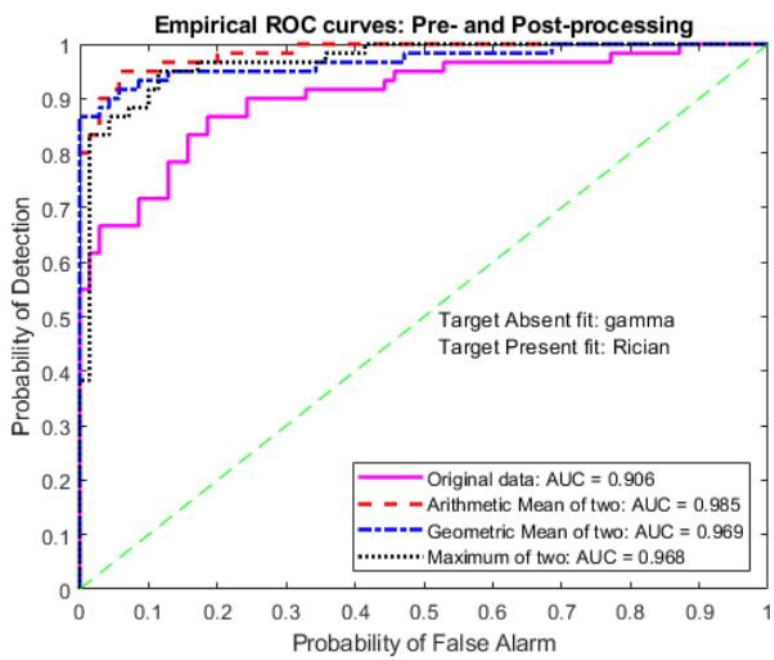
Part 3:

The goal is to improve target detection performance using signal processing techniques applied to synthetic datasets generated from the best-fitting distributions identified in Part 2. Two sets of data are generated using random number generators (with the estimated parameters), one set for the 'no target' and another set for the 'target present' matching the sizes of the original data. Treating the pair of 'no target' and 'target present' as independent, study the effect of (1) arithmetic mean (2) maximum and (3) geometric mean. In each case, the densities will be estimated along with a repetition of (a) estimation of areas under the ROC curve (b) positive predictive value at the threshold set from the given data (c) a performance index defined as:

$$\textit{performance index} = \frac{\left| \textit{mean}(\text{target\_absent}) - \textit{mean}(\text{target\_present}) \right|}{\sqrt{\text{var}(\text{target\_absent}) + \text{var}(\text{target\_present})}}$$

The entire process is repeated 100 times to calculate the mean and standard deviation of AUC, error rate, PPV, and performance index.


Original data
Performance Index = 1.303
Arithmetic mean
Performance Index = 2.107
Maximum
Performance Index = 1.817
Geometric mean
Performance Index = 1.918
Target Absent
Target Present
Estimated pdf
data


Empirical ROC curves: Pre- and Post-processing
Probability of Detection
Probability of False Alarm
Target Absent fit: gamma
Target Present fit: Rician
Original data: AUC = 0.906
Arithmetic Mean of two: AUC = 0.985
Geometric Mean of two: AUC = 0.969
Maximum of two: AUC = 0.968

Performance improvement metrics: Dual Diversity

Single iteration

	Target Not Detected	Target Detected	Signal Processing Algorithm
Target Absent	57	13	No Processing (input): PI = 1.303 *Error rate = 21/130, AUC = 0.906
Target Present	8	52	*Positive Predictive Value = 0.8
Target Absent	66	4	Arithmetic Mean: PI = 2.107 *Error rate = 7/130, AUC = 0.985
Target Present	3	57	*Positive Predictive Value = 0.934
Target Absent	62	8	Maximum: PI = 1.817 *Error rate = 11/130, AUC = 0.968
Target Present	3	57	*Positive Predictive Value = 0.877
Target Absent	70	0	Geometric Mean: PI = 1.918 *Error rate = 8/130, AUC = 0.969
Target Present	8	52	*Positive Predictive Value = 1

*Error rate and PPV estimated using Youden's index Threshold

Threshold = 3.2471 (Original data)
Threshold = 3.3399 (AM)
Threshold = 4.3545 (Max)
Threshold = 4.3975 (GM)

Performance Improvment from Signal processing (dual diversity)
Mean and Std. Deviation of metrics:100 Iterations

	Orig data	AM	MX	GM	
AUC	0.906	0.968	0.957	0.959	(mean)
		0.014	0.018	0.016	(std. dev.)
Error Counts [out of 130]	21	9	11	10	(mean)
		2	3	3	(std. dev.)
PPV	0.8	0.924	0.9	0.923	(mean)
		0.041	0.045	0.041	(std. dev.)
Perf. Index	1.303	1.827	1.721	1.72	(mean)
		0.188	0.184	0.187	(std. dev.)

Conclusion:

In conclusion, this project has demonstrated the importance of statistical analysis in enhancing the performance of machine vision and machine learning systems. Through ROC analysis, we were able to determine the optimal threshold for target detection, which minimized the error rates and maximized the positive predictive value. We achieved an initial AUC of of 0.906, an error rate of 21/130, and a positive predictive value (PPV) of 0.80. Hypothesis testing allowed us to model the statistical properties of the data, identifying Gamma distribution as the best fit for the "target absent" data and the Rician distribution for the "target present" data. Bootstrapping methods confirmed the robustness of these findings, with the mean AUC from parametric and non-parametric bootstrapping closely matching the empirical results. The 95% confidence interval for the AUC further validated the system's reliability. Finally, by applying signal processing techniques such as arithmetic mean, geometric mean, and maximum value, we significantly improved the system's performance metrics, including the area under the ROC curve (AUC), error rates, and positive predictive value.

The results indicate that signal processing methods, particularly the arithmetic mean, provided the most substantial improvement in performance, as evidenced by the increased AUC and reduced error rates. Arithmetic Mean achieved the highest improvement with a mean AUC of 0.985, an error rate of 7/130, and a PPV of 0.934. This project underscores the value of combining statistical analysis with signal processing to enhance the accuracy and reliability of machine vision systems. Future work could explore additional signal processing techniques and their impact on system performance, as well as the application of these methods in real-world scenarios.