Supplementary Information (SI) for Lab on a Chip.

Supplementary Information

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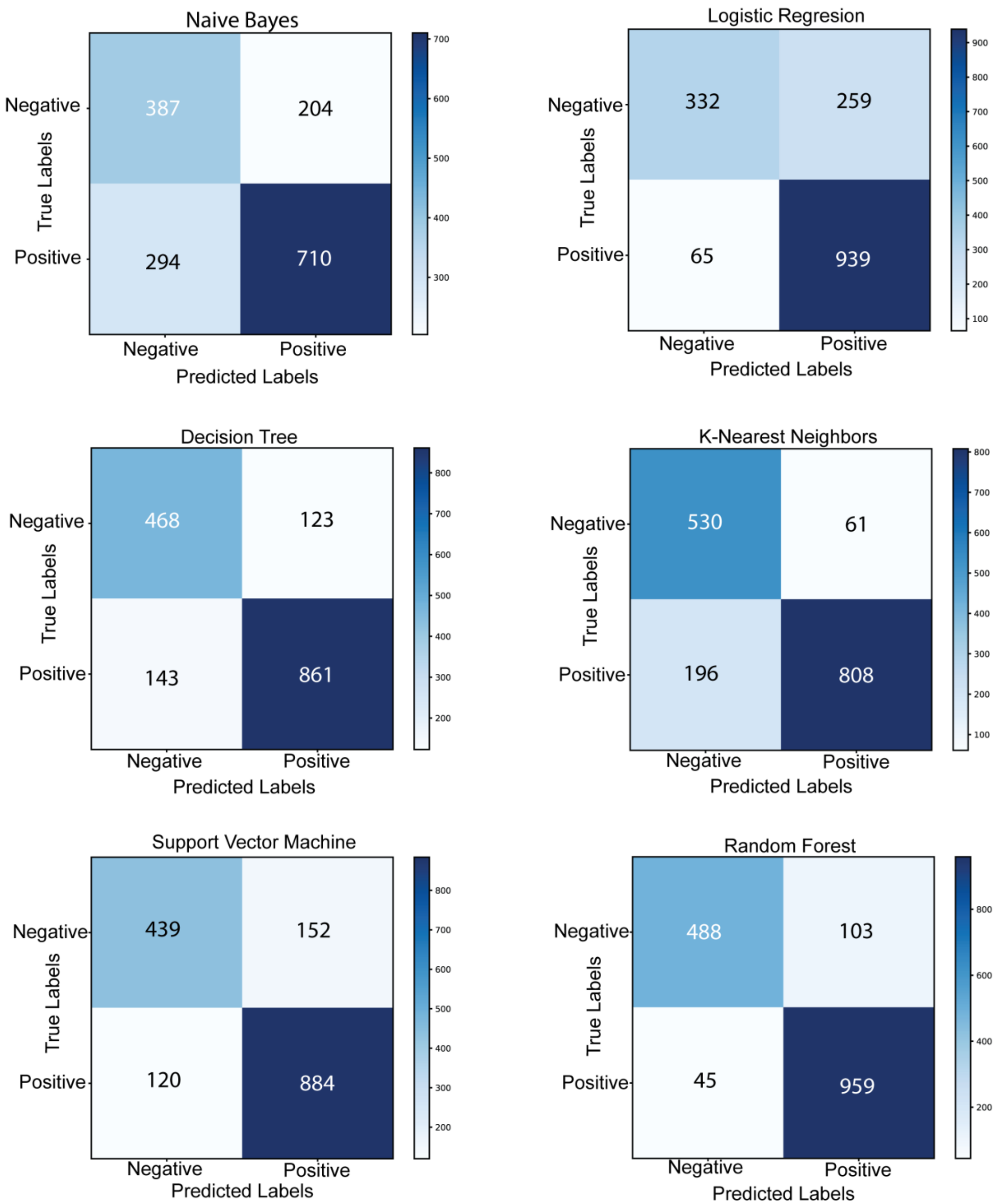
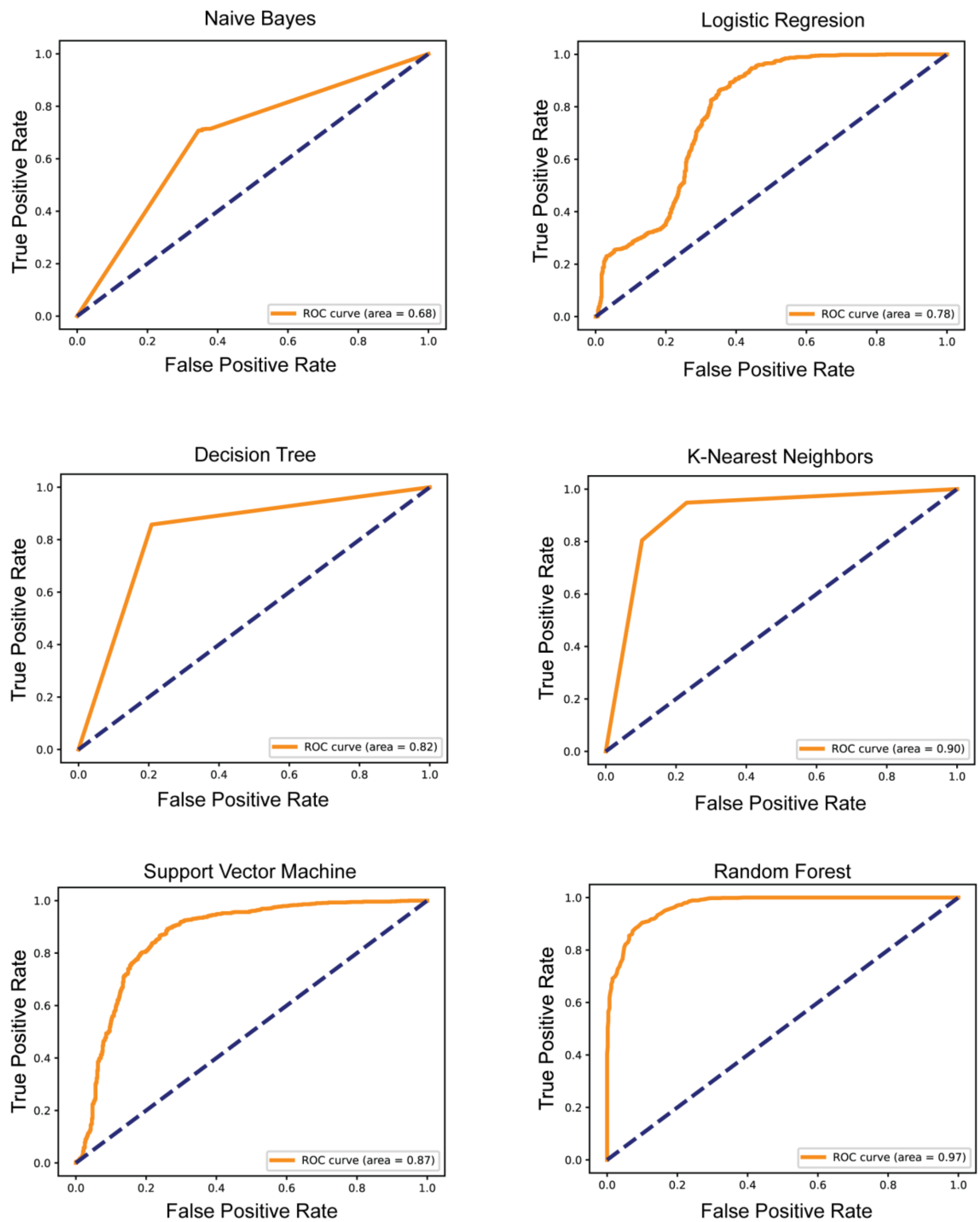
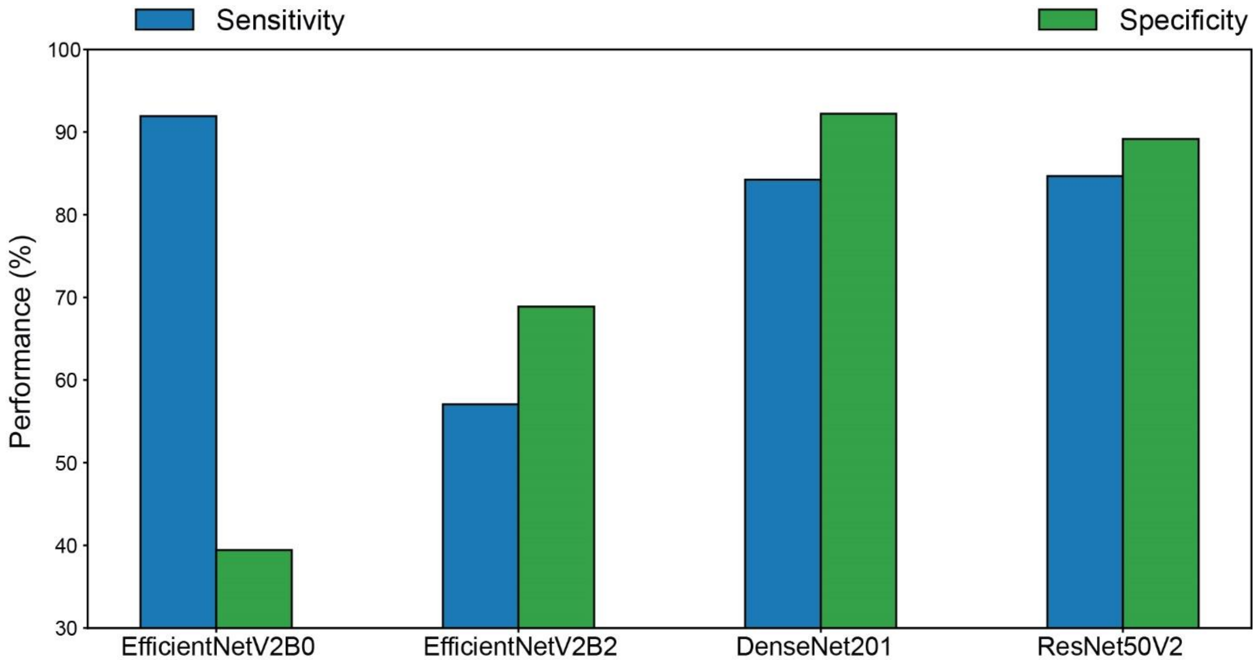
a. Supplementary Figures.



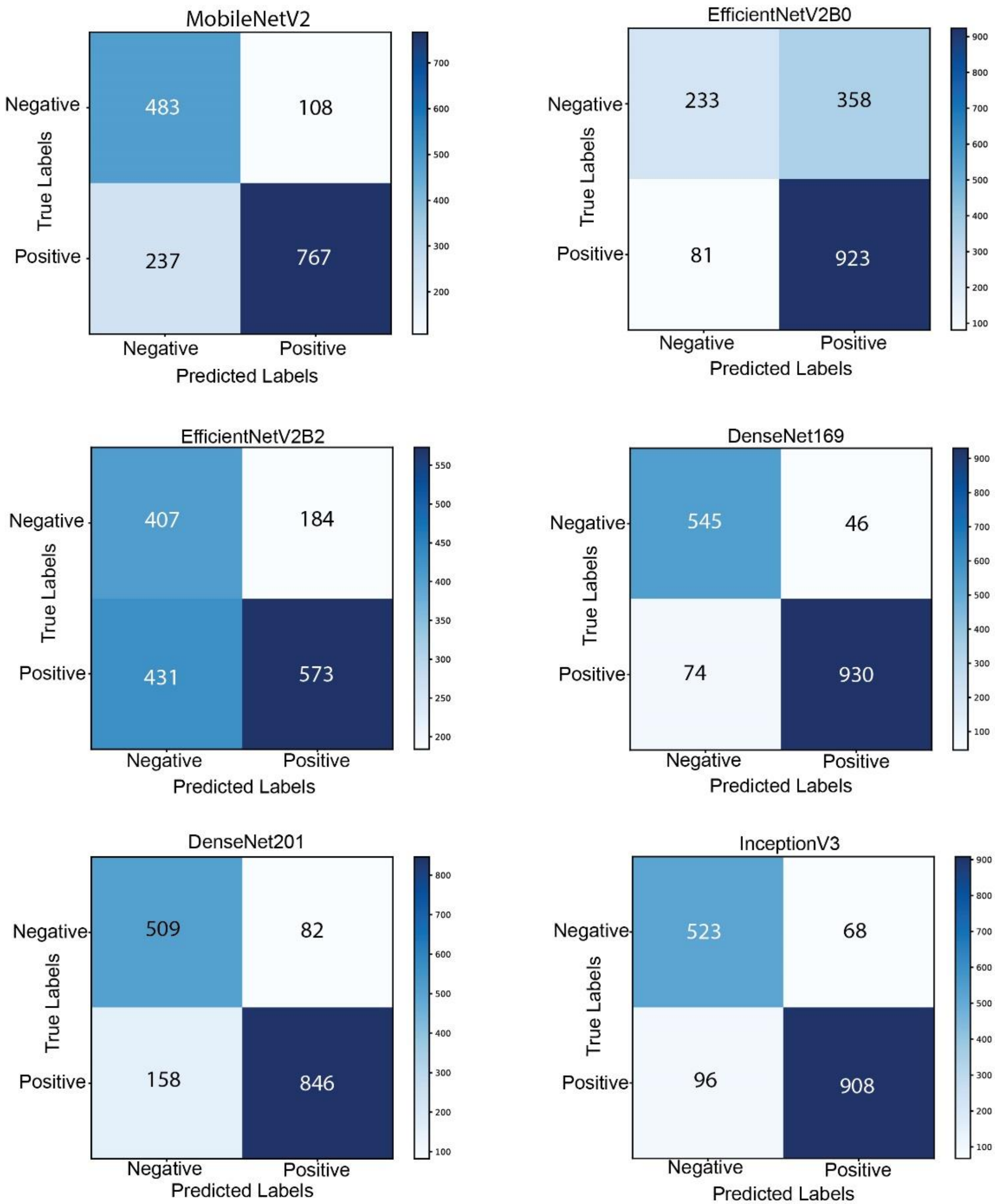
Supplementary Figure 1. Confusion matrix analysis of the tested machine learning algorithms.



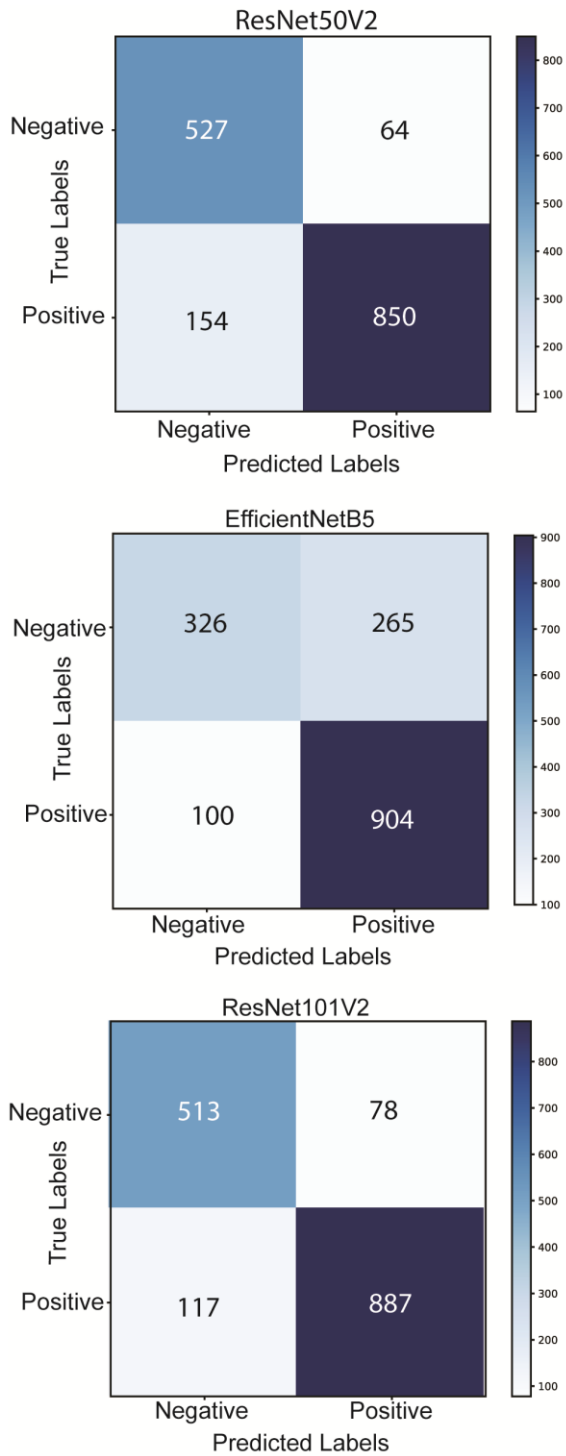
Supplementary Figure 2. ROC analysis of the tested machine learning algorithms.



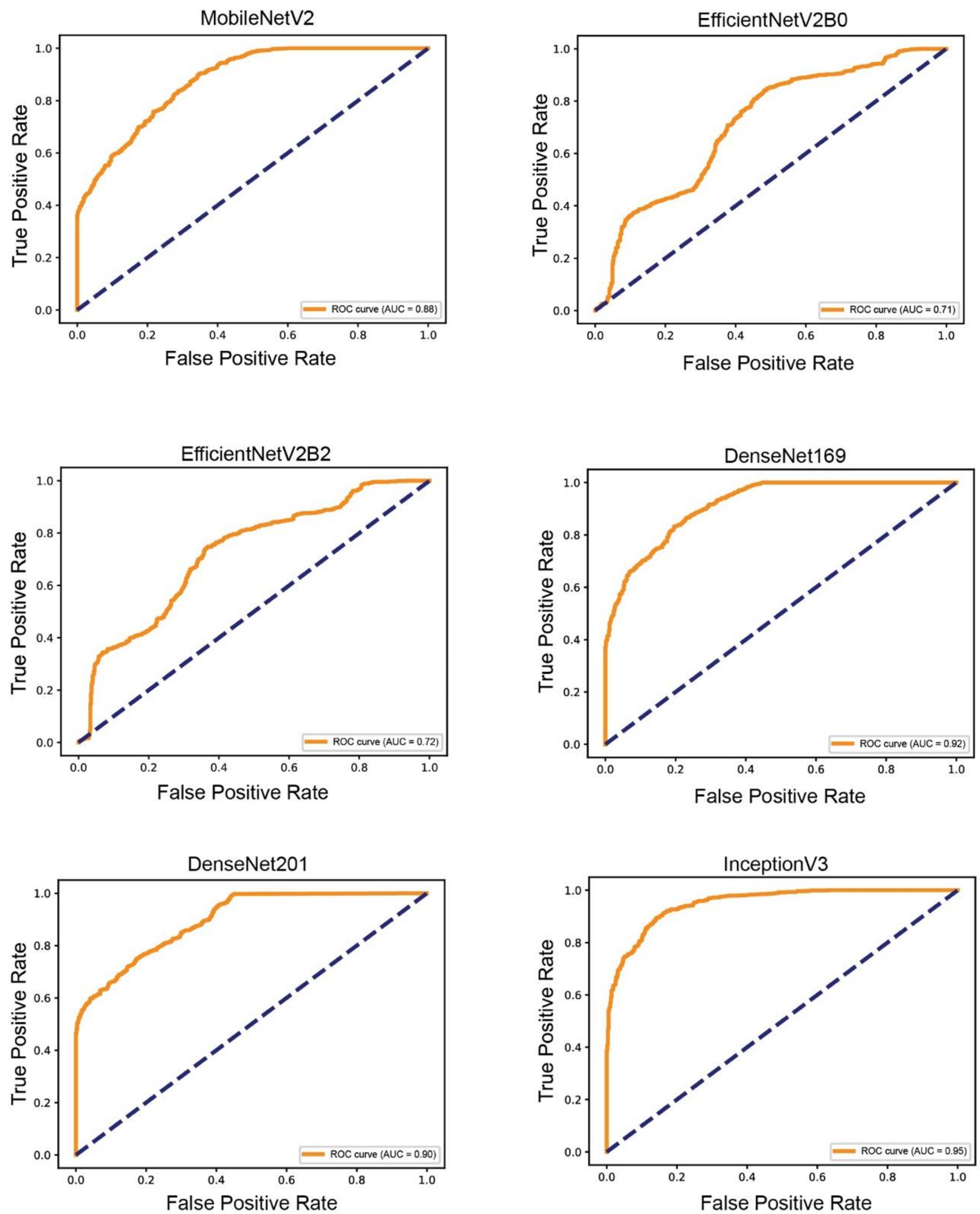
Supplementary Figure 3. Performance of deep learning models of EfficientNetV2B0, EfficientNetV2B2, DenseNet201, and ResNet50V2 in microfluidic testing.



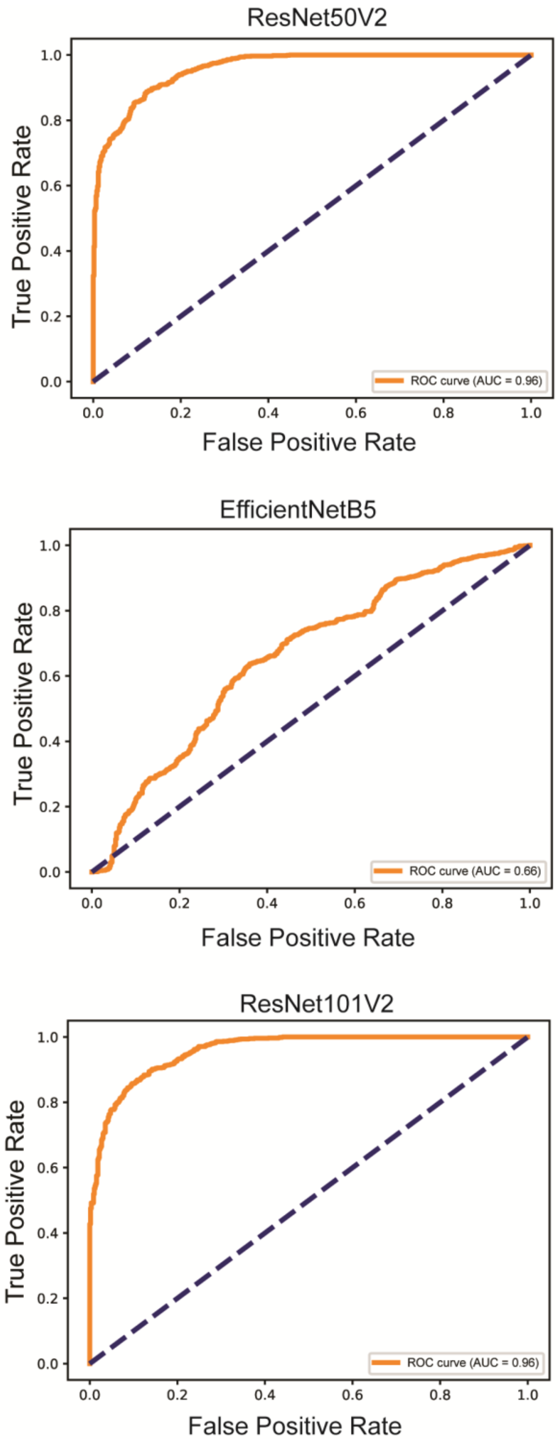
Supplementary Figure 4. Confusion matrix analysis of deep learning algorithms of MobileNetV2, EfficientNetV2B0, EfficientNetV2B2, DenseNet169, DenseNet201, and InceptionV3.



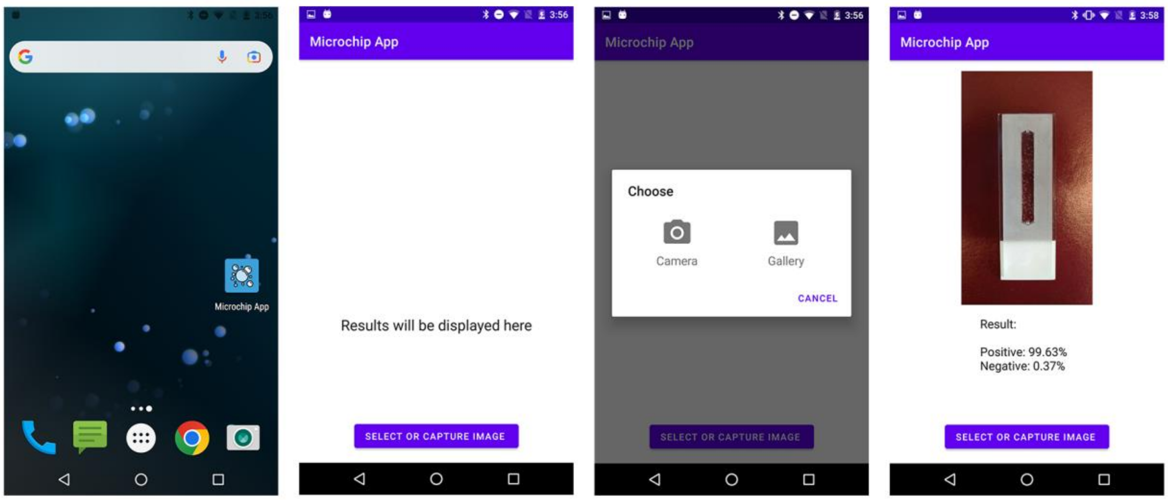
Supplementary Figure 5. Confusion matrix analysis of deep learning algorithms of ResNet50V2, EfficientNetB5, and Resnet101V2.



Supplementary Figure 6. ROC analysis of deep learning algorithms (MobileNetV2, EfficientNetV2B0, EfficientNetV2B2, DenseNet169, DenseNet201, InceptionV3).



Supplementary Figure 7. ROC analysis of deep learning algorithms (ResNet50V2, EfficientNetB5, Resnet101V2).



Supplementary Figure 8. The mobile application developed with DenseNet169 algorithm, facilitating the testing and classification of microfluidic chips. Users are presented with two distinct options for chip classification: the first option is selecting an image stored on phone, and the second option is starting the cellphone camera and testing sample.

b. Supplementary Tables

Supplementary Table 1. ML algorithms performance in microfluidic testing.

Models	Accuracy	Precision	Sensitivity	F1 Score	Specificity	MCC	AUC
Naive Bayes	0.6878	0.7768	0.7072	0.7404	0.6548	0.3534	0.68
Logistic Regression	0.7969	0.7838	0.9353	0.8529	0.5618	0.5551	0.78
Decision Tree	0.8332	0.875	0.8576	0.8662	0.7919	0.6452	0.82
K-Nearest Neighbors	0.8389	0.9298	0.8048	0.8628	0.8968	0.6804	0.9
Support Vector Machine	0.8295	0.8533	0.8805	0.8667	0.7428	0.6309	0.87
Random Forest	0.9072	0.903	0.9552	0.928	0.8257	0.7995	0.97

Supplementary Table 2. DL algorithms performance in microfluidic testing.

Models	Accuracy	Precision	Sensitivity	F1 Score	Specificity	MCC	AUC
MobileNetV2	0.7837	0.8766	0.7639	0.8164	0.8173	0.5641	0.88
EfficienNetV2B0	0.7248	0.7205	0.9193	0.8079	0.3942	0.3809	0.71
EfficienNetV2B2	0.6144	0.7569	0.5707	0.6508	0.6887	0.2509	0.72
DenseNet169	0.9248	0.9529	0.9263	0.9394	0.9222	0.8409	0.92
DenseNet201	0.8495	0.9116	0.8426	0.8758	0.8613	0.6892	0.9
InceptionV3	0.8972	0.9303	0.9044	0.9172	0.8849	0.7822	0.95
ResNet50V2	0.8633	0.93	0.8466	0.8863	0.8917	0.7209	0.96
EfficientNetB5	0.79	0.7665	0.9582	0.8517	0.5042	0.5453	0.66
ResNet101V2	0.8777	0.9192	0.8835	0.901	0.868	0.7424	0.96

Supplementary Table 3. Performance of ML comparted to DL in microfluidic testing under challenging conditions that simulate real-world sample testing.

Models	Accuracy	Precision	Sensitivity	F1 Score	Specificity	MCC	AUC
DenseNet169	0.882	0.9181	0.8419	0. 8784	0. 9231	0.7669	0.92
Random Forest	0.804	0.7798	0.8538	0.8151	0.7530	0.6103	0.87

Supplementary Table 4. AI performance in testing microfluidics at POC.

Models	Accuracy	Precision	Sensitivity	F1 Score	Specificity	MCC	AUC
App	0.848	0.9323	0.8105	0.8671	0.9072	0.7009	0.90