| Binary Classification Setup | Positive Class | False Positive (FP) | False Negative (FN) | More Serious (FP or FN) | Metric (Recall or Precision) | Data Imbalance |
|---|---------------------------------------|---|--|---|---|---|
| Spam Email Detection for Adult User | Email is spam | Algorithm detects email as spam, but it is not | Algorithm detects email as not spam, but it is spam | False Positive (important email could go to spam folder) | Precision (mini- mizing FPs) | Yes, fewer spam emails compared to non-spam emails |
| Spam Email Detection for Child User | Email is spam | Algorithm detects email as spam, but it is not | Algorithm detects email as not spam, but it is spam | False Negative (spam email could go to inbox) | Recall (minimizing FNs) | Yes, fewer spam emails compared to non-spam emails |
| Fraud Detection for International Credit Card Transactions | Transaction is fraudulent | Algorithm flags a transaction as fraudulent, but it is not | Algorithm does not flag trans- action that ends up being fraudulent | False Negative (missed fraudulent transaction can cause financial loss) | Recall (minimizing FNs) | Yes, fewer fraudulent transactions compared to legitimate ones |
| Fraud Detection for UPI Payment to Enter Into a Movie Theatre | Transaction is fraudulent | Algorithm flags a transaction as fraudulent, but it is not | Algorithm does not flag trans- action that ends up being fraudulent | False Positive (many legitimate transactions flagged as fraudulent may lead to many movie goers arguing with the ticketing staff) | Precision (minimizing FPs) | Yes, fewer fraudulent transactions compared to legitimate ones |
| Loan Default Prediction | Borrower will default on the loan | Algorithm predicts loan default, but borrower does not default | Algorithm predicts no loan default, but borrower defaults | False Negative (loan default not predicted can lead to financial losses) | Recall (minimizing FNs) | Yes, fewer default cases compared to successful loan repayments |
| Credit Card Approval | Credit card application is approved | Algorithm approves a card for someone who should not have been approved | Algorithm does not approve someone who should have been approved | False Positive (approving credit for someone who may default is riskier) | Precision (minimizing false positives) | Yes, fewer risky applicants compared to non-risky ones |
| Satellite Launch Day Selection | Day is approved as safe for launching | Algorithm approves a day as safe for launch and it turns out to be not | Algorithm does not approve a day as safe for launch and it turns out to be safe | False Positive (approving a risky day for launching may lead to serious consequences for the personnel in- volved) | Precision (minimizing false positives) | Depending on the time of the year it could be balanced or imbalanced |
| Bank Call Centre Call for Two-wheeler Loan Offer | Customer on call accepts loan offer | Algorithm predicts customer will accept offer, but ended up not accepting it | Algorithm predicts customer will not accept offer, but they would have actually accepted | False Negative (missing a customer who will have accepted the loan offer will lead to financial losses) | Recall (minimizing FNs) | Depends on whether the of- fer is for an electric two- wheeler (balanced) or not (im- balanced), for example |
| Airport Screening of Luggage for Explosives | Explosive is present | Algorithm predicts explosive is present, but it turned out to be a benign object; a laptop battery, for example | Algorithm predicts no explosive is present, but luggage actually has a harmful explosive | False Negative (a harmful explosive not predicted can lead to a great human loss) | Recall (minimizing FNs) | Yes, fewer luggage containing explosives compared to normal ones |
| Intrusion Detection | Network intrusion occurs | Algorithm flags an intrusion, but there was no intrusion | Algorithm does not detect an actual intrusion | False Negative (a missed intrusion can compromise the system) | Recall (minimizing false FNs) | Yes, fewer intrusion events compared to normal network activity |
| Customer Churn Prediction | Customer will churn | Algorithm predicts customer will churn, but they don't | Algorithm predicts customer won't churn, but they do | False Negative (failing to retain a churned customer could lose business) | Recall (minimizing FNs) | Typically balanced between churn and no-churn cases |
| Sentiment Analysis of Reviews | Review is positive | Algorithm classifies a negative review as positive | Algorithm classifies a positive review as negative | False Negative (missing a positive review in feedback analysis) | Recall (minimizing FNs) | Typically, roughly equal number of positive and negative reviews |
| Gender Recognition | Person is male | Algorithm identifies a person as male, but they are not | Algorithm identifies a person as not male, but they are | Depends on the application | Precision (if FP is more serious), Recall (if FN is more serious) | No, balanced distribution between male and female |

Sudarsan N.S. Acharya sudarsan.acharya@manipal.edu