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\[
\begin{array}{|c|c|c|c|c|c|}
\hline
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\hline
\text{D}_3 & \text{V}_1 & \text{Valid passport} & \text{Accuracy} & \text{Accuracy} & \text{Accuracy} \\
\hline
\text{D}_3 & \text{V}_2 & \text{Valid passport} & \text{Accuracy} & \text{Accuracy} & \text{Accuracy} \\
\hline
\text{D}_3 & \text{V}_3 & \text{Valid passport} & \text{Accuracy} & \text{Accuracy} & \text{Accuracy} \\
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<table>
<thead>
<tr>
<th>Training</th>
<th>Passport layers added</th>
<th>Passport layers added</th>
<th>Passport layers added</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>- Passport layers needed</td>
<td>- Passport layers needed</td>
<td>- Passport layers needed</td>
</tr>
<tr>
<td></td>
<td>- 15-30% more training time</td>
<td>- 100-125% more training time</td>
<td>- 100-150% more training time</td>
</tr>
<tr>
<td>Inferred</td>
<td>Passport layers &amp; passport needed</td>
<td>Passport layers &amp; passport needed</td>
<td>Passport layers &amp; passport needed</td>
</tr>
<tr>
<td></td>
<td>- NO extra time incurred</td>
<td>- NO extra time incurred</td>
<td>- NO extra time incurred</td>
</tr>
<tr>
<td>Verification</td>
<td>NO separate verification needed</td>
<td>NO separate verification needed</td>
<td>NO separate verification needed</td>
</tr>
<tr>
<td></td>
<td>- Trigger set needed</td>
<td>- Trigger set needed</td>
<td>- Trigger set needed</td>
</tr>
<tr>
<td></td>
<td>Passport layers &amp; passports needed</td>
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