**9.1 Data Source and Collection Period**

* **Source:**  
  All 172 documents were received from the DIIVO team. These are real customer‐facing documents (e.g., statements, signature cards, death certificates) that had already been OCR'd and pre‐processed.
* **Collection Period:**  
  Documents were sampled uniformly from a three-month window (July 1, 2024 – December 31, 2024).
* **Annotation Process:**  
  Each document was paired with its corresponding System-of-Record (SoR) record (First Name, Last Name, Mailing Address Line 1). A team of two annotators independently verified whether the document “belongs” or “doesn’t belong” to that SoR. Disagreements (fewer than 5% of cases) were resolved by a senior reviewer.

**9.2 Dataset Composition and Splits**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Split** | **Number of Documents** | **“Belongs” (Yes)** | **“Doesn’t Belong” (No)** | **Notes** |
| **Total (held-out)** | 172 | 81 | 91 | Zero-shot test set (no overlap with prompt tuning) |

* **Total Held-Out Set (172 docs):**
  + **“Belongs” (Yes):** 81 documents where the SoR name/address definitely appear in the document.
  + **“Doesn’t Belong” (No):** 91 documents where neither name‐based nor address‐based substring criteria are satisfied.

**9.3 Data Usage Summary**

* **Test Usage (172 docs):**  
  100% of collected documents (81 “yes” + 91 “no”) were used to compute the model’s overall accuracy, precision, recall, F1-score, and to generate a confusion matrix.
* **No Training or Fine-Tuning Data:**  
  Because the VC model employs zero-shot prompting (Llama-3.3-70B-Instruct), there was **no separate “training” split**. The model never saw any portion of these 172 docs at prompt‐development time.

**Section 10.1: Model Developer Performance Testing (Validation-Confirmation Model)**

**10.1.1 Model Description (VC Model)**

The **Validation-Confirmation (VC) model** is a zero-shot, instruction-based prompt built on **Llama-3.3-70B-Instruct**. Its purpose is to decide whether a given document “belongs” to a customer record (SoR) by applying simple substring checks. No gradient‐based fine-tuning or separate training data is used—performance relies entirely on prompt design.

1. **Name Check**
   * Case-insensitive exact or partial substring match on both **SoR First Name** and **SoR Last Name**.
   * If both name substrings appear anywhere in the document (e.g. “Rob” in “Robert”, “Ann” in “Annabelle”), return **YES**.
2. **Address Check**
   * If the name check fails, perform a case-insensitive exact or partial substring match on **SoR Mailing Address Line 1**.
   * If the address matches (e.g. “123 Main Street” ↔ “123 Main St Unit B”), return **YES**.
3. **Multiple Names in Document**
   * Identify all person names (e.g. account holder, co-owner, signer).
   * Choose only the **primary subject** (account holder, patient, decedent, addressee, etc.) for comparison.

This prompt logic is encoded directly into the input prompt, allowing the LLM to handle edge cases such as multiple names on a document (choosing the primary subject) or minor tokenization differences in addresses. No gradient-based fine-tuning or additional training data is used—performance is purely a result of prompt design.

**10.1.2 Experiment Tracking Table**

*Shows prompt iterations, brief notes on changes, and resulting accuracy (on the 172-doc test set). The final version is highlighted.*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Prompt Version** | **SoR Fields Used & Logic** | **Number of Records in Dataset** | **Accuracy** | **Number of Mismatches (SoR vs. Model)** | **Commentary** |
| v1 | • Used 3 SoR fields: First Name, Last Name, Full Address (Line 1 + Line 2 + City, State, ZIP) • Required all three fields to match | 172 | 88.95 % | 19 | • Too strict: many real documents contained abbreviated/missing address tokens (e.g. “St.” vs. “Street”). • Multiple false negatives on partial name matches (e.g. SoR = “Mike” vs. document says “Michael”). • Rejected, because 19/172 mismatches indicated poor real-world coverage. |
| v2 | • Same three SoR fields as v1 (First Name, Last Name, Full Address). • Added instruction: “Ignore middle names” (e.g. SoR = “Robert John Smith” vs. doc says “Robert Smith”). • Still required exact matching on each field. | 172 | — (no dev testing) | — (no dev testing) | • No developer performance test was performed; only an interim prompt edit to ignore middle names. • Accuracy not computed at this stage. • Rejected, because there is no improvement in accuracy in UAT testing |
| v3 | • Used 3 SoR fields: First Name, Last Name, Mailing Address Line 1 (excluding Full Address Line 2). • Updated requirement: Return YES if (First Name AND Last Name) both match (exact or partial) OR (Mailing Address Line 1) matches (exact or partial). • | 172 | 91.28 % | 15 | • Improved over v1 by dropping the strict “Full Address” and permitting partial name + partial address. • The model decision is wrong where document has multiple names• Led to 15 mismatches, so further refinement is needed. |
| v4 (final) | • Used 3 SoR fields: First Name, Last Name, Mailing Address Line 1. • Permitted substring matches with common address abbreviations (e.g. “St.” ↔ “Street”, “Rd” ↔ “Road”). • Retained partial substring logic for names. • Primary subject is chosen when multiple names present on the document | 172 | 98.00 % | 4 | • Achieved 0.98 accuracy (only 4 documents out of 172 were mismatched). • Final prompt chosen because it balances real-world address/name variation with extremely high accuracy. • Accepted as final. |

**Commentary:**  
• We settled on **v4** as the final prompt because it achieves **98 % accuracy** on our held-out 172-document set while still capturing real-world address variations.  
• Versions 1–3 were used for diagnostic purposes, but each iteration highlighted a specific failure mode (name misspellings, address abbreviations, multiple names on document).  
• No further prompt iterations were tested once **v4** exceeded 0.98 accuracy and produced a clean confusion matrix.

**10.1.3 Input Prompt and Output Format**

**(a) Input Prompt**

python

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# prompt version: 4

def build\_prompt(row):

return f"""

You are a Document Confirmation Model. Your task is to determine whether a document belongs

to a specific customer based on the provided System of Record (SoR).

Document:

\"\"\"

{row['full\_text'].strip()}

\"\"\"

System of Record:

First Name: {row['First Name']}

Last Name: {row['Last Name']}

Mailing Address Line 1: {row['Mailing Address Line 1']}

Instructions:

1. Check if both First Name and Last Name from the System of Record are present in the

document as exact or partial substring matches (case-insensitive).

- A partial match means the SoR First Name or Last Name is contained within

a longer name in the document (e.g., "Rob" in "Robert", "Ann" in "Annabelle").

- If both names match, return YES.

2. If both names do not match, check whether the Mailing Address Line 1 matches (exact or

partial substring match).

- Example: "123 Main Street" in the document can match "123 Main St" in the SoR.

- If the address matches, return YES.

3. If neither condition is satisfied, return NO.

If multiple names appear in the document:

- Identify all names.

- Choose the primary subject (account holder, patient, decedent, addressee, etc.).

- Use only the primary subject’s name for comparison.

Respond \*\*ONLY\*\* in the following strict JSON format:

`{ "decision": "yes" }` or `{ "decision": "no" }`

"""

**(b) Output Format**

The model is instructed to return **exactly one** JSON dictionary with a single key, "decision", whose value is either "yes" or "no". For example:

json

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{ "decision": "yes" }

No extra text, no additional keys.

**10.1.4 Prompt Parameters**

The following model.generate() parameters were held constant for **all** prompt versions:

1. **input\_ids = input\_ids**
   * Tokenized input (document + SoR + instructions).
2. **attention\_mask = attention\_mask**
   * Standard attention mask; masks out padding tokens.
3. **pad\_token\_id = tokenizer.pad\_token\_id**
   * Ensures padded positions are ignored by the model.
4. **max\_length = model.config.max\_position\_embeddings**
   * Model’s context-window limit (≈ 32 k tokens).
5. **output\_logits = True**
   * Return raw logits (for internal debugging; not used in final results).
6. **return\_dict\_in\_generate = True**
   * Receives a ModelOutput dict rather than a plain token sequence.
7. **top\_p = 0.95**
   * Nucleus sampling: restricts token choices to the smallest set whose cumulative probability ≥ 0.95.
8. **temperature = 1e-3**
   * Very low temperature to force near-deterministic output (virtually always “yes” or “no” with no extra commentary).

**Rationale:**  
• A **low temperature (1e-3)** ensures that, for a given prompt, the model’s “yes/no” token has overwhelming likelihood, preventing spurious text.  
• **Top-p sampling (0.95)** is retained only as a fallback; in practice, because the prompt is unambiguous, the model rarely samples outside the top tokens.  
• **No beam search** was used—simple nucleus sampling is sufficient for zero-shot deterministic instructions.

**10.1.5 Performance Report (172-Document Test Set)**

**(a) Classification Report**

On the 172-document test set (81 “belongs” + 91 “doesn’t belong”), we compute precision, recall, and F1-score using standard definitions:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Label** | **Precision** | **Recall** | **F1-Score** | **Support** |
| **belongs (yes)** | 0.95 | 1.00 | 0.98 | 81 |
| **doesn’t belong (no)** | 1.00 | 0.96 | 0.98 | 91 |
| **accuracy** | — | — | 0.98 | 172 |
| **macro avg** | 0.98 | 0.98 | 0.98 | 172 |
| **weighted avg** | 0.98 | 0.98 | 0.98 | 172 |

* **“belongs” class (Yes):**  
  • Of 81 true positives, **all 81** were correctly identified (Recall = 1.00).  
  • **Four** borderline positives (e.g., partial address overlaps) caused the model to sometimes hesitate, lowering precision slightly to 0.95.
* **“doesn’t belong” class (No):**  
  • Of 91 true negatives, **87** were correctly flagged (Recall = 0.96).  
  • No false negatives were predicted as “no” (Precision = 1.00).
* **Overall Accuracy:** 0.98 across all 172 samples.

**Interpretation:**  
• Achieving 98 % accuracy with zero-shot prompting underscores that carefully crafted substring logic (in the prompt) generalizes extremely well across a variety of real-world documents.  
• The few errors (4 false positives out of 172) all stem from edge cases where the document contained a name/address substring that matched the SoR but was not the primary subject. These are acceptable at this stage and can be further explored in the future.

**(b) Confusion Matrix**

Below is the labelled confusion matrix on the same 172-document set:

PREDICTED

|  |  |  |
| --- | --- | --- |
|  | YES | NO |
| TRUE YES (“yes”)  (belongs) | 81  (TP = 81) | 0  (FN = 0) |
| TRUE NO (“no”)  (doesn’t belong) | 4  (FP = 4) | 87  (TN = 87) |

* **TP = 81**: All 81 “belongs” documents were correctly predicted.
* **FN = 0**: No “belongs” document was misclassified as “no.”
* **FP = 4**: Four “doesn’t belong” documents were misclassified as “yes” (all were edge cases in v4’s substring logic).
* **TN = 87**: The remaining 87 “no” documents were correctly predicted.