Task-B Enhancement Plan

Healthcare Named Entity & Event Extraction

1. Caching Mechanisms for Processed Documents

Objective

Reduce processing latency and computational cost by reusing results for documents that have been previously processed, either in full or in part.

Approach

- Implement a two-tier caching system:
 - o In-Memory LRU Cache for hot results.
 - Persistent Redis/SQLite Store for warm/cold data across sessions.
- Use content hashing (SHA-256) of normalized text combined with rule_version and model_version as the cache key.
- Enable **partial-document caching** by segmenting documents into logical sections (e.g., *History*, *Medications*, *Labs*).
- Set TTL expiry and allow manual purge via an admin endpoint.

Implementation

- Create a CacheService integrated into /api/extract and /api/upload.
- On cache hit → return stored JSON results immediately.
- On cache miss → process normally, store results with metadata (created at, expires at).
- Integrate Prometheus metrics:
 - cache_hit_rate, cache_miss_rate, avg_latency_saved_ms.

Quantified Benefits

- Latency Reduction: 50–70% for repeat/overlapping documents.
- **CPU-Hour Reduction**: ~40% for workloads with ≥30% repetition.
- Target Cache Hit Rate: ≥60% for batch ingestion scenarios.

2. Pre-trained Domain-Specific Language Models (Hybrid Pipeline)

Objective

Enhance extraction accuracy by combining the precision of rule-based methods with the contextual understanding of transformer-based language models trained on biomedical corpora.

Approach

- Integrate ClinicalBERT, BioBERT, or distilled equivalents for NER and event extraction.
- Apply hybrid fusion:
 - Rule-First: Accept high-confidence rule matches, then expand or correct with ML model predictions.
 - Confidence Fusion: Merge outputs using calibrated thresholds (thresholds.json).
- Use **ONNX export** and **INT8 quantization** for efficient CPU inference.

Implementation

- Add HybridPipeline wrapper to execute rules and model in parallel.
- Store model weights in /models/ directory; load at app startup.
- Enable or disable via config flag: enable_ml_model = true|false.
- Maintain a calibration set for periodic threshold tuning.

Quantified Benefits

- NER Macro-F1 Improvement: +8–12 percentage points for MEDICATION, DISEASE, SYMPTOM.
- Event Trigger Recall: +10–15% with <5% precision drop.
- Latency Target: ≤250 ms/doc on CPU after quantization.

3. Distributed Processing for Large Collections

Objective

Scale the system horizontally to handle millions of documents efficiently.

Approach

- Use Celery + RabbitMQ (or Redis Queue) for distributed task execution.
- Partition workloads at document or section level.
- Ensure **idempotency** by using content-hash job keys.

Implementation

- Bulk upload handler enqueues file references to a message broker.
- Worker processes load the same extraction pipeline as the real-time API.
- Persist results to the DB or object store; index for search and analytics.
- Implement fault tolerance: retries with exponential backoff, dead-letter queue.

Quantified Benefits

- **Throughput**: 100–150 docs/min per worker (2 KB average).
- **Scalability**: Linear up to 50 workers with <5% coordination overhead.
- **SLA Compliance**: 95% of jobs within batch processing window.

4. Relation Extraction Between Domain Entities

Objective

Identify clinically relevant relationships between extracted entities (e.g., *MEDICATION—treats—DISEASE*).

Approach

- Pattern-Based Candidate Generation using domain-specific lexical cues (e.g., "treated with").
- **ML-Assisted Classification** for relation validation using entity type, context embeddings, and dependency parsing features.

Implementation

- Add relation_extractor.py after NER & event extraction.
- Output graph-ready JSON: { subject_id, predicate, object_id, evidence, confidence }.

Provide /api/relations endpoint for UI consumption.

Quantified Benefits

- **Precision**: ≥80% for top 5 relation types.
- **Recall**: ≥70% on curated evaluation set.
- Analyst Time Saved: ~30% less manual chart review.

5. Temporal Reasoning for Event Sequencing

Objective

Accurately order and normalize events to produce patient timelines for longitudinal analysis.

Approach

- Normalize both **absolute** and **relative** time expressions (e.g., "post-op day 2").
- Handle event intervals (start-end) and instantaneous events (admission, surgery).

Implementation

- Add temporal_normalizer.py after event extraction.
- Return enriched event objects with t_start, t_end, confidence.
- Provide /api/timeline endpoint; render via vis.js timeline component.

Quantified Benefits

- Correct Sequencing: ≥90% accuracy in test timelines.
- Ambiguity Resolution: ≥85% for relative time expressions.

6. Visualization Tools for Entities, Relations & Timelines

Objective

Improve user insight and trust via interactive visualizations.

Approach

- Entity-Relation Graph using D3.js.
- Event Timeline with zoom and filter controls.
- Analytics Dashboard with co-occurrence heatmaps, latency charts, cache hit rates.

Implementation

- Extend /api/export to output graph/timeline JSON.
- Add PHI-safe evidence tooltips in UI.
- Implement role-based access control for sensitive views.

Quantified Benefits

- Finding Recall: +15–20% compared to text-only review.
- Interpretation Time Reduction: 25–40% in user tests.

7. Phased Roadmap

Phase 0 (Week 0-1) - Baseline & Caching

• Implement caching layer, integrate metrics, measure baseline KPIs.

Phase 1 (Week 2-4) – Hybrid Model Integration

Add transformer model, calibrate fusion thresholds, run A/B tests.

Phase 2 (Week 5-7) – Distributed Processing

• Deploy Celery workers, tune throughput, enhance observability.

Phase 3 (Week 8-10) - Advanced Analysis & Visualization

• Deploy relation extraction, temporal reasoning, and rich visual dashboards.

8. KPIs & Acceptance Criteria

Quality

- +8–12 pp Macro-F1 for MEDICATION/DISEASE/SYMPTOM.
- ≥0.80 F1 for event triggers.

Performance

- p95 latency ≤600 ms for short notes.
- Cache hit rate ≥60%.
- Batch throughput ≥100 docs/min/worker.

User Experience

• ≥4/5 satisfaction score for clarity of highlights, graphs, and timelines.

9. Risks & Mitigations

- Model Drift → Schedule evaluations, enable quick rollback via config flags.
- **PHI Exposure** → Redaction pipeline, encrypted storage, RBAC.
- **Cost Spikes** → Autoscaling caps, off-peak batch scheduling.
- Integration Bugs → Shadow testing, blue/green deployments.

10. Integration Discussion

The proposed enhancements will integrate seamlessly into the **existing Flask-based Healthcare NER + Event Extraction pipeline** as follows:

- Caching → Introduced as a pre-processing check in /api/extract and /api/upload, bypassing tokenization and model inference on cache hits.
- Hybrid Model Pipeline → Wrapped around existing rule-based extraction in HybridPipeline, with configurable toggle and calibration logic for merging outputs.
- Distributed Processing → Bulk ingestion path modified to push jobs into a Celery queue; worker containers run identical extraction code to ensure consistency between real-time and batch modes.
- Relation Extraction → Added as a post-processing step after entity/event extraction, feeding into both the API (/api/relations) and frontend graph view.
- Temporal Reasoning → Appended after event extraction; produces normalized timelines for /api/timeline and feeds timeline visualization in the UI.
- Visualization Tools → Frontend templates extended with new tabs for graph and timeline views; backend extended to provide JSON data feeds for these components.
- Metrics & Monitoring → All components emit metrics (latency, throughput, hit rates, F1 scores) to Prometheus; Grafana dashboards updated for new KPIs.

Conclusion

This enhancement plan not only addresses performance, accuracy, and analytical depth but also ensures that each feature is **practically integrated** into the current architecture without disrupting existing workflows. The phased approach minimizes risk and maximizes measurable impact.